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Review Article

A Review: Current Trend of Immersive Technologies for Indoor Navigation and the Algorithms

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ABSTRACT

The term "indoor navigation system" pertains to a technological or practical approach that facilitates the navigation and orientation of individuals within indoor settings, such as museums, airports, shopping malls, or buildings. Over several years, significant advancements have been made in indoor navigation. Numerous studies have been conducted on the issue. However, a fair evaluation and comparison of indoor navigation algorithms have not been discussed further. This paper presents a comprehensive review of collective algorithms developed for indoor navigation. The in-depth analysis of these articles concentrates on both advantages and disadvantages, as well as the different types of algorithms used in each article. A systematic literature review (SLR) methodology guided our article-finding, vetting, and grading processes. Finally, we narrowed the pool down to 75 articles using SLR. We organized them into several groups according to their topics. In these quick analyses, we pull out the most important concepts, article types, rating criteria, and the positives and negatives of each piece. Based on the findings of this review, we can conclude that an efficient solution for indoor navigation that uses the capabilities of embedded data and technological advances in immersive technologies can be achieved by training the shortest path algorithm with a deep learning algorithm to enhance the indoor navigation system.

Keywords: Augmented reality, deep learning, indoor navigation, mixed reality, shortest path, virtual reality

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INTRODUCTION

In current navigation systems, electronic devices are used to determine the user's location, find the most direct route, and, in certain cases, automatically direct vehicles to their destinations. The science and technology of spotting a sailboat, airplane, or other types of vehicles and directing them to a specific location are known as navigation (Kunhoth et al., 2020). In today's world, most navigational aids depend on satellite signals transmitted by the global positioning system (GPS). While GPS works perfectly outside, it is difficult to use inside due to several factors, such as reduced signal strength, dim lighting, and complicated environments. Recent discussions have brought up potential new directions for the development of indoor navigation, including the use of image-based and Wi-Fi-based systems. GPS is ineffective for determining the location inside a building due to the absence of a line of sight (NLoS), weak signal strength, and reduced accuracy (Syazwani et al., 2022). Although GPS performs admirably in open areas, its performance in urban canyons is notoriously poor because of the signal reflections of NLOS satellites (Z. Liu et al., 2022).

There are numerous applications for indoor navigation systems, such as in universities, complex malls, bus stations, train stations, airports, libraries, and museums. Furthermore, specific navigation applications for humans and people with visual impairments benefit from internal navigation systems. Unlike exterior areas, indoor areas are more difficult to navigate due to the absence of reliable GPS signals and physical obstacles like walls, stairs, and furniture. Different obstacles are present in interior environments, increasing the difficulty of implementing navigation systems.

The fundamental components of a human indoor navigation system consist of three elements, namely the indoor positioning system (IPS) module, the navigation module, and the human-machine interaction (HMI) module. The system for indoor positioning is designed to approximate the user's location. At the same time, the navigation element determines which routes are the most efficient to take from the user's present location to the destination they have in mind. The Human Machine Interface (HMI) module makes engaging with the system easier and allows users to give commands. The efficiency of GPS-based indoor positioning is limited; hence, alternative methods such as those based on computer vision (Lee et al., 2022), pedestrian dead reckoning (PDR) (Jiang et al., 2022), and radio frequency (RF) (Syazwani et al., 2022) signals are employed for indoor positioning.

Various technologies can be utilized for indoor positioning, including but not limited to Wi-Fi (Chan et al., 2023), Bluetooth (Babakhani et al., 2021), *radio frequency identification* (Chumkamon et al., 2008), ZigBee (Dong et al., 2018), ultra-wideband (Sarkar et al., 2021), and a geomagnetic field (Yeh et al., 2020). These technologies require specific equipment, resulting in a high implementation cost. Wi-Fi boasts a notable advantage despite potential drawbacks due to its widespread integration and prevalence across various devices. The popularity of ultra-wideband (UWB) technology in high-precision indoor positioning systems can be attributed to its advantages over narrowband-based technologies such as Bluetooth and Wi-Fi. UWB offers a wide variety of benefits, including a high data transfer rate, low transmission energy, a short signal transmission length, and deep penetration (Che et al., 2023).

One of the most important aspects of indoor navigation is that it may be applied in a variety of different contexts involving people (Abdallah et al., 2022). However, there is a significant challenge when the concept is applied to multiple rooms and obstacles in the indoor environment. The layout of an indoor navigation system's user interface is critical. Most electronic navigation systems still use a conventional interface; thus, users must actively compare on-screen arrows with their surroundings to identify the right position. For example, with indoor mapping tools, students may easily find their way to class or any other location on campus. However, if they are new to the campus, they may soon feel lost among the maze of buildings and departments in a typical university.

The use of augmented reality (AR), virtual reality (VR), and mixed reality (MR) technologies for indoor navigation presents a promising area of research that provides diverse opportunities for improving navigation in interior environments. Industry-wide adoption of AR indoor navigation is increasing (Verma et al., 2020). Technology firms have started investing in AR due to its appealing features and compatibility with other devices. Currently, AR can be used in many different environments, such as in the classroom, the workplace, a museum, a factory, a store, or a museum shop. Furthermore, AR has been rigorously tested and investigated, and indoor navigation is just one of its applications. By using image recognition technology to calculate the location and angle of the acquired image actuarially, AR enables the virtual world on the screen to blend with and interact with real-world situations.

The application of VR for indoor navigation is currently a thriving field of research and development. Indoor navigation utilizing VR is an active research and development topic. It entails using VR technology to assist users in navigating and orienting themselves within indoor environments. Virtual reality is a scenario generated by a computer that simulates a realistic experience. Popular online maps provide primarily two-dimensional views of the tops of buildings—the interiors of a location become difficult to envision. Indoor navigation utilizing VR technology solves the issue of visualizing the interior infrastructure of vast, complex structures (Khan et al., 2020).

The term MR denotes a continuum that encompasses both VR and AR. This technology integrates elements of reality with virtual objects or surroundings to generate a blended experience for individuals. This technology is more user-friendly, adaptable, and productive compared to more conventional methods of navigating within a building. Even though this technology is still in its infancy, it is already abundantly evident that it will flourish in the years to come (El-Sheimy & Li, 2021).

The implementation of algorithms is vital for navigating inside buildings. Indoor navigation systems depend on algorithms as their primary component because they provide precise mapping and localization, efficient path planning, and real-time adaptation. Algorithms are a very important component in making interior navigation accurate, efficient, and user-friendly. Although various alternative algorithms have been used for indoor navigation, the ones discussed in this article are the shortest path and deep learning algorithms. The problem of discovering the shortest way or route between an origin point and an endpoint is frequently referred to as the issue of the shortest path. In most cases, the challenge of the shortest path is represented through graphs. A graph is an example of an abstract mathematical entity comprising many collections of vertices and edges. Edges connect two adjacent vertices. It is possible to walk along the edges of a graph by moving from one vertex to another. A graph's edges provide a path for walking from one vertex to another. The presence or absence of the ability to walk along the edges in both directions distinguishes between a directed graph and an undirected graph. There are several different algorithms designed to solve the issue of the shortest path, including but not limited to Dijkstra's algorithm (P. Liu et al., 2022), the Bellman-Ford algorithm (Parimala et al., 2021), the A* algorithm (Rachmawati & Gustin, 2020), the D* algorithm (Alves et al., 2019), and the Floyd-Warshall algorithm (Ramadiani et al., 2018).

Deep learning is a specialization within the larger area of machine learning. It uses an artificial neural network (ANN) architecture to spot patterns and calculate feature extraction. Many studies have proposed combining a variety of indoor navigation techniques and algorithms. Most analyses investigated the use of various shortest-path algorithms. Location awareness and remembering navigation (LARN) and flexible path planning (FPP) are among the algorithms used for indoor navigation systems.

The evolution of technology for navigation inside buildings is faced with several significant challenges, including imprecise positioning (Nessa et al., 2020), intricate and ever-changing surroundings (Varma & Anand, 2021), restricted scalability and adaptability (Zlatanova et al., 2013), obstructions within indoor spaces and signal interference (El-Sheimy & Li, 2021), and limited connectivity (Trybała & Gattner, 2021). In order to tackle these obstacles, a blend of technological advancements, algorithmic enhancements, data management tactics, and user-focused design methodologies is necessary. Ongoing research and progress in positioning technologies, machine learning, and data fusion techniques are directed toward surmounting these obstacles and enhancing indoor navigation systems' precision, user-friendliness, and dependability.

Additionally, deep learning techniques allow for indoor navigation that is accurate and responsive to adjustments in the surrounding environment, such as the presence of obstacles or changes in lighting conditions (Shahbazian et al., 2023). These factors can affect the accuracy and reliability of the algorithm, especially if it has not been trained in a wide range of environments and scenarios. Another challenge is the computational complexity of deep learning algorithms, which may require significant computing resources and time to train and optimize. It can be a significant barrier for researchers with limited access to computing resources, as well as for real-time applications where speed and efficiency are critical. Finally, there is also a need for standardized evaluation metrics and benchmarks to compare the performance of different deep-learning algorithms for indoor navigation systems. Currently, there is a lack of consensus on the most appropriate metrics and benchmarks, making it difficult to compare and replicate results across different studies.

One of the common problems in recent research on indoor navigation using deep learning algorithms is the absence of identified training information. In order to properly learn and generalize patterns and correlations between features, deep learning algorithms require enormous amounts of labeled data to work. However, obtaining labeled data for indoor navigation can be challenging and time-consuming, as it requires manually labeling the floor plans, indoor maps, and trajectories of users. Next, this article discusses the most recent developments in immersive technologies such as AR, VR, and MR. In addition to that, this research emphasized the algorithm that has been implemented in the indoor navigation system. Deep learning and shortest path algorithms are the two categories into which the algorithms have been divided due to the use of a number of different technological innovations and techniques. The goal of shortest-path algorithms is to identify the most direct route between two nodes in a network, while the objective of deep learning is to learn and anticipate complicated patterns.

CURRENT TRENDS OF IMMERSIVE TECHNOLOGIES IN INDOOR NAVIGATION

Indoor navigation systems are rapidly incorporating immersive technologies such as VR, AR, and MR to improve the user experience and deliver navigation solutions that are both more user-friendly and immersive. Augmented reality superimposes digital information over a user’s view of the physical world, enabling users to get real-time visual signals and directional information (Rehman & Cao, 2017). Augmented reality wayfinding applications have the capability to superimpose navigational instructions, arrows, or markers over the user’s vision of the indoor space, directing the user to their desired location.

VR’s immersive and participatory nature makes it a viable option for interior navigation. When used indoors, traditional GPS navigation might be difficult because of the reduced availability and accuracy of satellite signals. Virtual reality can help with these issues by simulating indoor navigation and constructing virtual representations of indoor spaces (B. Liu et al., 2021).

Mixed reality allows users to engage with virtual and physical objects. With this technology, it is possible to create the illusion that the virtual and physical worlds coexist.

Virtual markers, routes, or annotations can be superimposed over the user's environment to serve as interactive navigation instructions and directions when using an MR device like Microsoft HoloLens or Magic Leap One for interior navigation (B. Liu et al., 2022).

INDOOR NAVIGATION USING AUGMENTED REALITY

Augmented reality indoor navigation systems provide users with a more natural and immersive experience by fusing digital information with the physical world (Verma et al., 2020). By superimposing digital data (e.g., visual cues, directions, or annotations) onto a user's perspective of the real world, AR provides a more enriching experience. For example, Saeliw et al. (2022) developed an AR-based mall navigation utilizing AR Core, which directs visitors to the exhibition's location and provides them with the opportunity to experience and enjoy the virtual things in the mall.

Furthermore, according to Yang and Saniie (2017), the system that is being proposed will make use of devices with cameras, such as smartphones, to deliver position information by scanning AR markers that have been placed in the environment. It will ultimately assist users in being more aware of where they are. Chidsin et al. (2021) proposed a marker-free system for AR-based indoor navigation. The suggested system utilized the red-green blue-depth (RGB-D) camera to monitor the surroundings, and the technology known as simultaneous localization and mapping (SLAM) was utilized to generate a point cloud map (Lee et al., 2017). An indoor navigation system was implemented with the help of the Internet of Things devices available in the building and AR technology to direct people out of the building in the event of a fire.

Rehman and Cao (2017) proposed an AR-based indoor localization application with the goal of assisting people in navigating around areas that are entirely indoors. The software may be installed on a wide variety of computers, mobile phones, as well as wearable computers. Yoon and Lee (2023) proposed an idea for AR logistics software that can be used on s(smartphones. The application would lead the user to the appropriate logistical area at a building site. The logistical program was coded in Unity 3D, based on the AR Foundation foundation for AR, as well as the ZXing library, which is used to recognize QR codes. Saeliw et al. (2022) address a reasonable alternative, architecture, and how technology has advanced to construct an indoor navigation system application using AR for shopping malls.

INDOOR NAVIGATION USING VIRTUAL REALITY

VR technology can be effectively utilized to innovate indoor positioning systems. Yuan et al. (2023) implemented an indoor fire evacuation simulated in virtual reality using a navigation grid's corner points. The VR simulation of the evacuation of the interior fire crowd was implemented on the basis of the dynamic layout of the route taken by firefighters evacuating from a building with many exits. Khan et al. (2020) proposed an indoor navigation system for stadiums using WebVR technology and offering users an experience that is wholly immersive and compelling. With the assistance of 360-degree photos, the “virtual shortest path” to the location of interest is presented.

In addition, VR equipment can furnish fully immersive learning environments and provide interactive learning opportunities for teams working together in a shared space. By using VR, the unattractiveness and lack of interest in conventional teaching approaches can be overcome. Guo et al. (2020) recommended using a method to evacuate a large group of people using virtual reality simulations in the event of an indoor fire with several exits. For many years, the field of health sciences has focused on improving interior navigation methods for people who are blind or have other visual impairments. Real and Araujo (2021) developed a tool for validating navigation instructions and another tool for user training for the PERCEPT system.

In conclusion, VR can make indoor navigation easier, which is especially beneficial in complicated places like airports, malls, and stadiums. The widespread adoption of VR technology has the potential to completely alter the environment of indoor navigation.

INDOOR NAVIGATION USING MIXED REALITY

The application of MR technology, which enhances the existing physical environment by displaying digital holograms and supplying supplementary details, shows promise for use in indoor navigation. An appropriate strategy has the potential to enhance the development of MR-based indoor navigation applications as well as related research. For example, B. Liu et al. (2021) provided user studies with an overview of magnetic resonance MR technology, equipment, and the design of MR-based indoor navigation systems.

In addition, MR will also provide a better experience for the user based on real-time navigation. Chung et al. (2021) used a gadget called Microsoft HoloLens to construct a head-mounted museum navigation system by merging several technologies, such as MR, gesture recognition, and location awareness.

Next, MR can be employed for indoor rescue operations by providing rescuers real-time data about the inside environment and the position of people needing rescue. This system employs augmented indoor maps and MR to improve the speed and effectiveness of rescue teams reacting to and dealing with unexpected hazards (Chae et al., 2023).

It is one of the studies that used MR for indoor navigation (B. Liu et al., 2021). The system was created, developed, and put into operation with virtual semantic landmarks in interior spaces based on MR. Additionally, users were evaluated to investigate whether such markers can aid in the acquisition of spatial information when navigating.

Microsoft HoloLens was used to analyze the inside environment and give data to be used as an indoor navigation aid (B. Liu et al., 2021). HoloLens is an AR helmet that uses

MR technology to provide users with holographic images that blend with the context of their surroundings.

MR-based indoor navigation systems can give users accurate and reliable help when navigating indoor environments. However, additional research is required to make position monitoring more accurate and to design user interfaces that are easy to use and intuitive. Table 1 shows the summary work of immersive technologies for indoor navigation.

Table 1
Summary work of immersive technologies of indoor navigation

Type of Immersive Technology	Year	Title/Project Name	Strengths	Weaknesses
AR	2022	FIND: Mall navigation using augmented reality (Rochadiani et al., 2022)	i. Attract more visitors ii. Easy to use	i. High cost ii. No direction arrow
AR	2017	Indoor navigation for the visually impaired using AR markers (Yang & Saniie, 2017)	i. Highly accurate ii. The system provides voice instruction	i. Users must be trained to use the AR marker system effectively
AR	2021	AR-based navigation using RGB-D camera and hybrid map (Chidsin et al., 2021)	i. Real-time navigation ii. Easy to use	i. High-cost ii. No audio instruction
AR	2017	Indoor navigation system for evacuation route in case of fire by using environment and location data (Lee et al., 2017)	i. Increased safety ii. Quick evacuation	i. High-cost ii. The system may estimate a person's location incorrectly
AR	2017	Augmented reality-based indoor navigation: A comparative analysis of handheld devices vs. Google Glass (Rehman & Cao, 2017)	i. Low cost ii. User-friendly	i. Limited battery life ii. Wearable devices and smartphones failed the memory tests
AR	2023	Development of a Construction-Site Work Support System Using BIM-Marker-Based Augmented Reality (Yoon & Lee, 2023)	i. Low cost ii. Low implementation effort	i. Obstacles in constructing paths have not yet been considered
AR	2021	Research direction for Android-based indoor navigation solution for shopping malls through augmented reality-EasyMap (Rubio-Sandoval et al., 2021)	i. User-friendly ii. Real-time navigation	i. High-cost ii. Limited coverage

Table 1 *(continue)*

Type of Immersive Technology	Year	Title/Project Name	Strengths	Weaknesses
VR	2023	Application of navigation grid corner point algorithm in virtual reality simulation images of indoor fire evacuation (Yuan et al., 2023)	i. Virtual reality can solve the situation of multiple indoor exits and dynamic environmental factors ii. Quick evacuation	i. Cannot predict others' evacuation routes or completely comprehend the current situation's threats
VR	2020	Indoor navigation in stadium using virtual reality (Khan et al., 2020)	i. WebVR offers an immersive experience with a 360-degree image view	i. Security issue
VR	2020	A virtual reality simulation method for crowd evacuation in a multi-exit indoor fire environment (Guo et al., 2020)	i. Real-time	i. The user's VR experience is seamless only when the frame rate is stable over 60 fps
VR	2017	Ves: A Mixed-Reality Development Platform Of Navigation Systems For the Blind And Visually Impaired (Real & Araujo, 2021)	i. Improve the user's experience in the actual world by letting them explore and learn before they arrive	i. The system lacks an interface for orientation and mobility instructors to alter the environment by specifying points of interest and exploratory activities
MR	2022	Designing mixed reality-based indoor navigation for user studies (B. Liu et al., 2021)	i. Helps researchers construct a research-oriented MR-based indoor navigation system in more generic situations	i. MR technology struggles to map transparent objects and display holograms in bright lighting conditions
MR	2021	Development of a head-mounted mixed-reality museum navigation system (Chung et al., 2021)	i. Real-time ii. Increase the efficiency of navigation	i. The system is limited to being used at Tamsui Oxford College of Aletheia University only
MR	2023	Design of a mixed reality system for simulating indoor disaster rescue (Chae et al., 2023)	i. Efficient at making rescues work more rapidly	i. The system compatibility is only for one device
MR	2021	Spatial knowledge acquisition with virtual semantic landmarks in mixed reality-based indoor navigation (B. Liu et al., 2021)	i. Enhance incidental spatial information development, although consumers believe better holograms would benefit them more	i. The device is heavy

Table 1 *(continue)*

Type of Immersive Technology	Year	Title/Project Name	Strengths	Weaknesses
MR	2022	Designing Mixed Reality-Based Indoor Navigation for User Studies (B. Liu et al., 2021)	i. High accuracy ii. Have a navigator to help users	i. These approaches might not always be effective in real life due to logistical or technological limitations

INDOOR NAVIGATION ALGORITHM

A literature review on indoor navigation systems has been conducted in this part of the article. It summarizes the research done in this area in the past. According to the published research, a considerable number of researchers have utilized different algorithms, such as Dijkstra (Z. Liu et al., 2021), A*(Wang et al., 2022), Bellman-Ford (Tamimi, 2015), Floyd Warshall (Ramadiani et al., 2018), Node2vec (Grover & Leskovec, 2016), recurrent neural networks (RNN) (Hoang et al., 2019), convolutional neural networks (CNN) (Gong et al., 2021), deep neural networks (DNN) (Oh & Kim, 2021) and artificial neural networks (ANN) (Jamil & Kim, 2019) to navigate inside buildings.

The classification of indoor navigation algorithms is depicted in Figure 1. By using a variety of technologies, the algorithms have been segmented into two categories: deep learning and shortest-path algorithms. Most prior research has concentrated on the shortest path and deep learning algorithms separately, whereas no studies have investigated both algorithms together.

The shortest path algorithm is a fundamental technique for identifying the most efficient route between two points in a graph. This route is determined by finding the

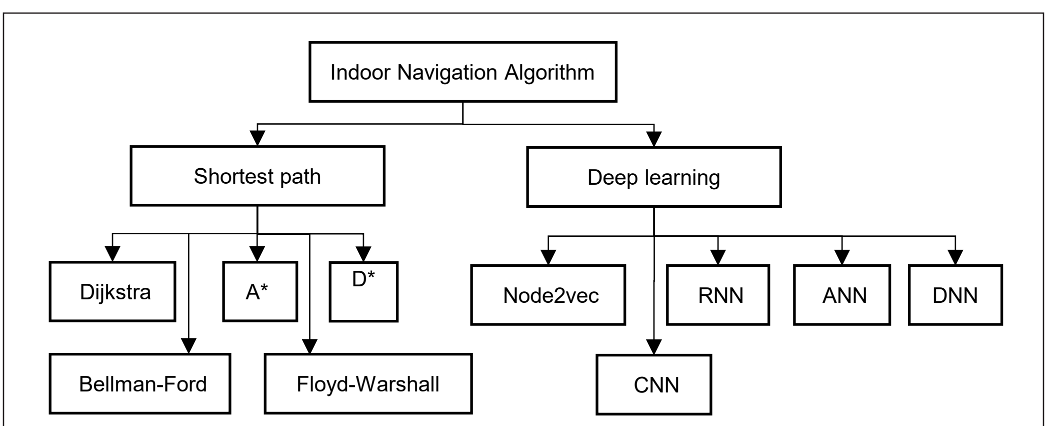

Figure 1. Indoor navigation algorithm taxonomy

smallest distance between the two locations. The graph represents the layout of the indoor environment in the context of indoor navigation. The graph nodes present specific places (e.g., rooms, corridors, or intersections), while the edges present the connections that link these locations (Rizi et al., 2018).

Using multiple deep learning techniques allows for performance to be improved based on prior experience. It will assist in improving accuracy and finding more ideal paths, depending on the experience gained. For example, Al-habashna et al. (2022) proposed a technique that can extract the received signal strength indicator (RSSI) from user equipment (UEs) and then utilize it to develop a fingerprint database using the information. The RSSI data of the UEs is then sent into a deep learning algorithm, which generates an estimate of the locations of the UEs within the building. Ge et al. (2022) developed a platform for collecting environmental sensing data and used environmental data for machine learning on location awareness in a building to improve location awareness.

Woensel et al. (2020) applied deep learning techniques with knowledge-based algorithms and instruments to accurately determine the precise position of an individual and its semantic relation to the determined location. Wu et al. (2020) applied image classification in deep learning to achieve the positioning function, and an algorithm was used to determine the most effective route to your destinations. The calculation results were then presented in the form of an interior navigation system.

Bakale et al. (2020) suggested deep learning to identify objects in the provided indoor scene and then used reinforcement learning to find a path. The suggested solution has provided the navigation path for approximately 2 minutes and 10 seconds.

THE TYPES OF ALGORITHMS FOR INDOOR NAVIGATION

The articles surveyed and presented in the Indoor Navigation Algorithm section demonstrate that the current research has concentrated on both algorithms, which determine where a person is located using deep learning and the shortest distance between two points. Table 2 shows the types of shortest-path algorithms for indoor navigation, and Table 3 presents the types of deep-learning algorithms.

Table 2
The shortest path algorithm for indoor navigation

Title/Project Name	Year	Algorithms	Results
Design and Implementation of the Optimization Algorithm in the Layout of Parking Lot Guidance (Z. Liu et al., 2021)	2021	Dijkstra	Determined the source node's lowest total weight (distance)
An improved Dijkstra-based algorithm for resource-constrained shortest path (P. Liu et al., 2022)	2022	Dijkstra	Determined the shortest path

Table 2 *(continue)*

Title/Project Name	Year	Algorithms	Results
Reliability study on the adaptation of Dijkstra's algorithm for gateway KLIA2 indoor navigation (Samah et al., 2020)	2020	Dijkstra	Determined the shortest route from the current location to the point of origin
Analysis of Dijkstra's algorithm and A∗ algorithm in shortest path problem (Rachmawati & Gustin, 2020)	2020	Dijkstra and A*	Dijkstra and A* have different loop counts depending on the number of points (nodes) in the graph
Indoor navigation using A* algorithm (Kasim et al., 2016)	2016	A*	A* uses a statistical function to find a better path, while Dijkstra's method just looks at all possible routes
The EBS-A* algorithm: An improved A* algorithm for path planning (Wang et al., 2022)	2022	A*	EBS-A* algorithm reduced the critical nodes by 91.89%, right-angle turns by 100%, and path planning efficiency by 278%
Analysis of path planning algorithms for service robots applied in indoor environments (Jia, 2023)	2019	A*	The A* search is a more straightforward option and can improve traditional path planning algorithm
Indoor Navigation with Human Assistance for Service Robots Using D∗Lite (Alves et al., 2019)	2018	D*	D*Lite can quickly and effectively replan a new path.
Bellman-Ford algorithm for solving the shortest path problem of a network under a picture fuzzy environment (Parimala et al., 2021)	2021	Bellman-Ford	The Bellman-Ford algorithm solves the shortest path issue under uncertainty in fuzzy image environments
A study on the Bellman-Ford shortest path algorithm using a global positioning system (Rai, 2022)	2022	Bellman-Ford	Dijkstra's algorithm and Bellman-Ford algorithm determine the graph's shortest path and optimize GPS
Floyd-Warshall algorithm to determine the shortest path based on Android (Ramadiani et al., 2018)	2018	Floyd-Warshall	Floyd-Warshall algorithm finds the fastest and shortest path between two nodes, whereas the program finds the path of more than two nodes
Comparison Studies for Different Shortest Path Algorithms (Tamimi, 2015)	2015	Dijkstra's, A*, Bellman-Ford and Floyd-Warshall	All of these algorithms are useful in different situations (e.g., the Floyd-Warshall algorithm functions as an adaptive and a multi-source shortest-path algorithm)

Table 3
The deep learning algorithm for indoor navigation

Title/Project Name	Year	Algorithms	Results
Node2vec: Scalable feature learning for networks (Grover & Leskovec, 2016)	2016	Node2vec	Node2vec is flexible and can handle changes

Table 3 *(continue)*

Title/Project Name	Year	Algorithms	Results
An improved collaborative filtering algorithm based on node2vec (Liang & Tang, 2018)	2018	Node2vec	Node2vec, graph attention networks, and multi-layer perceptrons find pivots with path lengths close to the shortest alternative route
A convolutional neural network feature detection approach to autonomous quadrotor indoor navigation (Garcia et al., 2019)	2019	CNN	CNN-based recognition of objects makes it easy to distinguish between a building structure and a person
Indoor positioning algorithm based on improved convolutional neural network (Zhou et al., 2022)	2022	CNN	The CNN algorithm is extremely reliable
Indoor localization with Wi-Fi fingerprinting using convolutional neural network (Jang & Hong, 2018)	2018	CNN	The CNN-based model is quicker and less time-complex than the current technique
Design and development of an indoor navigation system using a denoising autoencoder-based convolutional neural network for visually impaired people (Jothi & Sabeenian, 2022)	2022	CNN	DAECNN outperforms other previous classification methods.
DeepNav : A scalable and plug-and-play indoor navigation system based on visual CNN (Gong et al., 2021)	2021	CNN	DeepNav can be set up fast and has an average mistake in location of 2.3 m
DeepLoc : A deep neural network-based indoor positioning framework (S. Liu et al., 2021)	2021	DNN	DeepLoc can help enhance the accuracy of localization and achieve better efficiency
Deep neural network-based Wi-Fi/pedestrian dead reckoning indoor positioning system using adaptive robust factor graph model (Wang et al., 2020.)	2019	DNN	The DNN-based system is more reliable and accurate under different motion movements
The indoor positioning system using fingerprint method-based deep neural network the indoor positioning system using fingerprint method based deep neural network (Malik et al., 2019)	2019	DNN	The effectiveness of a DNN is proportional to the sum of its hidden layer sizes
Applying deep neural network (DNN) for robust indoor localization in multi-building environments (Adege et al., 2018.)	2018	DNN	DNN is capable of accurately localizing Wi-Fi users in wireless environments that are both hierarchical and complex
Wi-Fi-based indoor positioning system using deep neural network (Giney et al., 2020)	2020	DNN	DNN works better than other machine-learning algorithms
Deep neural network for indoor positioning based on channel impulse response (Dao & Salman, 2022)	2020	DNN	DCNN reduces the optimal ADE by half compared to the situation without optimal AP locations

Table 3 *(continue)*

Title/Project Name	Year	Algorithms	Results
DNN-based Wi-Fi positioning in 3GPP indoor office environment (Oh & Kim, 2021)	2021	DNN	DNN has a high accuracy for indoor localization
A deep autoencoder and RNN model for indoor localization with variable propagation loss (Espindola et al., 2021)	2023	RNN	RNN model improves the positioning accuracy
Bluetooth direction finding using recurrent neural network (Babakhani et al., 2021)	2021	RNN	RNN method produces fewer errors with higher accuracy
Centimeter-level indoor Localization using channel State Information with Recurrent Neural Networks (Yu et al., 2020)	2020	RNN	RNN estimate values more accurately than tree-based approaches
Recurrent neural networks for accurate RSSI indoor localization (Hoang et al., 2019)	2019	RNN	LSTM framework performs better than feedforward neural network with 0.75 m average localization error and 80% of mistakes under 1 m
Towards the implementation of recurrent neural network schemes for Wi-Fi fingerprint-based indoor positioning (Hsieh et al., 2018)	2018	RNN	RNN and LSTM algorithms predict sensor floor with excellent accuracy
Wireless fingerprinting uncertainty prediction based on machine learning (Li et al., 2019)	2019	ANN	ANN can predict wireless fingerprinting uncertainty and adaptive measurement noises in integrated localization EKF work
Artificial neural networks for navigation systems: a review of recent research (Jwo et al., 2023)	2023	ANN	The full ANN research was examined for integrating the INS with GNSS and using ANNs in navigation systems
Improving the accuracy of the alpha-beta filter algorithm using an ANN-based learning mechanism in indoor navigation system (Jamil & Kim, 2019)	2019	ANN	An ANN-based learning module was developed to improve the prediction accuracy of the alpha-beta filter algorithm as a case study.

DISCUSSION AND ANALYSIS OF SHORTEST-PATH ALGORITHMS

Indoor navigation is a challenging task that requires efficient algorithms to find the shortest path between two points. Based on Table 2, several studies have proposed different algorithms to address this issue. Dijkstra's algorithm is one of the most commonly used algorithms for indoor navigation (Z. Liu et al., 2021; P. Liu et al., 2022; Rachmawati & Gustin, 2020; Samah et al., 2020). It determines the shortest path between graph nodes. Other algorithms have addressed Dijkstra's shortcomings. The researchers decided on Dijkstra's and A* algorithms because they provide the quickest route to their objective. It has been demonstrated that modifying Dijkstra's algorithm can provide the shortest route for indoor navigation, starting from the current place and ending at the desired site.

A* algorithm uses a statistical function to determine a better path, while Dijkstra's algorithm considers all feasible routes (Kasim et al., 2016). EBS-A* algorithm reduced the number of important nodes by 91.89 %, the number of right-angle turns by 100 %, and the efficiency of path planning by 278 %. In addition, the shortest path problem that arises in environments with fuzzy images can be resolved with the help of the Bellman-Ford method (Parimala et al., 2021). Dijkstra's algorithm and the Bellman-Ford algorithm, which optimizes GPS and finds the shortest path through the graph, are utilized in the process (Rai, 2022). The Floyd-Warshall method determines the quickest and shortest path between any two nodes, while the algorithm determines the path between any number of nodes (Ramadiani et al., 2018). Dijkstra's, A*, Bellman-Ford and Floyd-Warshall algorithms are useful in different situations. For instance, the Floyd-Warshall algorithm can perform the duties of both adaptive and multi-source shortest-path algorithms (Tamimi, 2015).

In conclusion, indoor navigation algorithms have been proposed to identify the shortest way to the selected destination. Dijkstra's algorithm is the most widely used, whereas the A*, Bellman-Ford, and Floyd-Warshall algorithms have been presented to solve their weaknesses. Hybrid algorithms that mix techniques can also increase the shortest path accuracy (Alani et al., 2020).

DISCUSSION AND ANALYSIS OF DEEP LEARNING ALGORITHM

The ability of CNN to learn and identify visual features included within maps or floor layouts shows that it offers great promise. Garcia et al. (2019) performed CNN-based detection and localization of the structural characteristics of a corridor on an off-board platform, where the method independently guided a quadrotor through hallways with intersections and dead ends. Zhou et al. (2022) introduced the CNN-LOC system, which provides precise and reliable indoor localization via Wi-Fi fingerprint and CNN. Otherwise, CNN-based Wi-Fi fingerprint systems demonstrated their capability to provide a higher level of accuracy compared to deep learning-based multi-floor-multi-building classifiers currently in use (Jang & Hong, 2018). Jothi and Sabeenian (2022) utilized a denoising auto-encoder based on the convolutional neural network (DAECNN) to determine the current position of the users. Gong et al. (2021) presented DeepNav, a new indoor navigation system that relies solely on visual CNN to perform large-scale navigation. In order to facilitate rapid deployment, DeepNav uses a deployment strategy that only requires a single pilot.

Node2vec is a method for algorithmic learning used for representational purposes on graphs. It learns a continuous classification model for the nodes of any graph, which may then be used for a variety of other machine-learning tasks further down the line (Grover & Leskovec, 2016). In optimizing a neighborhood-preserving objective, the Node2vec framework can discover low-dimensional representations for the nodes that make up a graph (Liang & Tang, 2018).

It is possible to use deep neural networks (DNN) for indoor navigation by first training them to understand and categorize various aspects of indoor surroundings, such as partitions, entrances, and furniture, and then employing these data to estimate the user's current location and direct them to the destination of their choosing. S. Liu et al. (2021) presented a system based on DNNs (DeepLoc) to enable Wi-Fi fingerprint location. In addition, a DNN-based Wi-Fi/PDR indoor positioning system that uses a highly adaptive and robust factor-graph model was suggested for the indoor placement of smartphones to obtain a system that is more reliable and accurate under a variety of motion gestures (Wang et al., 2020).

In Malik et al. (2019), the DNN algorithm was suggested to enhance the fingerprint technique implemented in the IPS. Next, to accomplish precise localization in Wi-Fi situations, researchers suggested using DNNs (Adege et al., 2018.). Giney et al. (2020) used DNN and more traditional machine learning algorithms for categorizing 22-square grids representing different places.

Additionally, researchers have developed a deep CNN to predict the position of a moving robot. One of the input parameters of this network is a measurement of the channel's impulse response (Dao & Salman., 2022). Furthermore, DNN was suggested for application in the location positioning process within an indoor office environment by the 3rd generation partnership project (3GPP) (Oh & Kim, 2021).

Recurrent neural networks are well-suited to handle time-series data, typically in indoor navigation, as the user's location and motions change continuously throughout the navigation session. For example, Espindola et al. (2021) used a deep autoencoder and an RNN to develop a new method of indoor localization optimized for situations with varying propagation losses.

Babakhani et al. (2021) produced a design for the angle of arrival (AoA) estimation that uses a robust and fast signal processing method and a tiny RNN model to improve performance by approaching AoA estimation as a time-series problem. Yu et al. (2020) applied RNN for indoor localization. The suggested approach uses channel state information (CSI) data as features and considers the user's trajectory and the signal-to-noise ratio.

Furthermore, RNN has been proposed for Wi-Fi fingerprinting and indoor localization. The approach considers the relationship between a number of RSSI measurements and treats the user's movement as a single problem (Hoang et al., 2019). Hsieh et al. (2018) analyzed the effectiveness of RNN as a method of deep learning that could be applied in an indoor location system, particularly for the Wi-Fi fingerprinting dataset.

In conclusion, indoor navigation algorithms have become an essential tool for the user inside the building to find the right path to the desired destination accurately. Deep learning and shortest path algorithms are two of the most popular algorithms used for indoor navigation. Deep learning algorithms use various data sources to create detailed maps of buildings and locate a person, while shortest path algorithms find the quickest route between two points within a building. By using these algorithms, indoor navigation systems can provide accurate and efficient navigation within large buildings.

CONCLUSION

In the past six years, research into indoor navigation has been consistently active. This paper conducts an in-depth analysis of related articles, focusing on their strengths and weaknesses, as well as analyzing the algorithm types that have been implemented. The use of algorithms for indoor navigation has become an indispensable component in daily life. Shortest path and deep learning algorithms have become two of the most prominent types of algorithms used for indoor navigation. Deep learning algorithms use a variety of data sources to produce precise maps of buildings and locate a person. In contrast, shortest path algorithms determine the most direct path between two spots within a building in the smallest amount of time. With the assistance of these algorithms, indoor navigation systems can deliver precise and time-saving navigation around enormous structures.

The article is divided into the appropriate classifications and outlines several appealing alternatives for the continuation of future research. Indoor navigation is a difficult task involving complicated maps, advertising, and directional cues. Extended reality (XR) technologies, which include VR, AR, and MR, have the potential to revolutionize the process of navigating indoor spaces by giving consumers an experience that is both comprehensive and accessible.

In future work, by looking at this research gap, it is anticipated that this research will enable a new exploration of combining deep learning into the shortest path method by utilizing XR technology. This investigation will also help the XR developers choose the suitable algorithm they want to implement in the product for development and commercialization.

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