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Optimization of Indoor Navigation Using the A Algorithm and Adaptive Grid (Gridadapte) for Efficient Pathfinding

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ABSTRACT

Optimal path navigation in indoor environments is a crucial problem in the development of robotic systems and location-based services due to complex spatial structures, the presence of obstacles, and limited available pathways. The A* algorithm, as a heuristic-based pathfinding method, is widely used; however, its performance degrades on high-resolution grid maps because of the increasing number of nodes that must be explored. This study proposes the integration of the A* algorithm with an adaptive grid simplification method (Gridadapte) to improve pathfinding efficiency without sacrificing route quality. The research methodology includes grid-based indoor map modeling, the application of Gridadapte to reduce cell density in low-obstacle areas, and the implementation of the A* heuristic function for optimal path search. Performance evaluation is conducted through simulations on several indoor map scenarios by comparing conventional A* and Gridadapte-based A* in terms of the number of explored nodes, path length, and computation time. Simulation results show that the proposed approach significantly reduces the number of search nodes by 30–45% and accelerates computation time by 25–40% compared to A* on regular grids, while the resulting path length remains optimal and does not experience a significant increase. These findings indicate that Gridadapte is effective in reducing the A* search space while preserving the topological structure of the environment. Therefore, the combination of A* and Gridadapte is proven to enhance both the efficiency and accuracy of pathfinding in complex indoor environments. This approach has strong potential for application in autonomous robotic systems, smart building guidance systems, and location-based Internet of Things (IoT) applications in indoor settings such as hospitals, campuses, and shopping malls.

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INTRODUCTION

The development of navigation systems and digital mapping technologies has advanced rapidly in response to the growing demand for accurate and efficient route-finding solutions. In outdoor environments, Global Positioning System (GPS)–based navigation has been widely adopted; however, in indoor environments this approach is unreliable due to signal attenuation, complex building structures, and limited available pathways. Therefore, the development of indoor navigation systems based on map modeling and pathfinding algorithms has become a crucial research area in robotics, intelligent systems, and the Internet of Things (IoT) (Liu et al., 2020; Zhang & Li, 2019).

The A* (A-Star) algorithm is one of the most widely used heuristic-based pathfinding methods due to its ability to efficiently determine optimal paths. This algorithm combines the actual cost from the starting point to a given node with a heuristic estimate of the cost from that node to the goal, thereby minimizing the total path cost (Hart, Nilsson, & Raphael, 1968). In various navigation and robotics applications, A* has been proven to be more efficient than uninformed search methods such as Breadth-First Search or Dijkstra's algorithm in terms of the number of evaluated nodes and convergence speed (Russell & Norvig, 2021).

However, in high-resolution grid-based indoor mapping, the A* algorithm often encounters high computational complexity because the number of nodes that must be explored becomes extremely large, especially in buildings with many rooms, corridors, and obstacles (Sturtevant, 2012). This condition leads to increased computation time and memory consumption, thereby limiting the applicability of A* in real-time systems such as mobile robots and location-guidance systems.

To address this issue, various approaches have been developed to simplify spatial representations, one of which is the adaptive or hierarchical grid method. This approach allows simple areas to be represented using larger grid cells, while complex areas retain higher resolution, thus preserving environmental structure (Yap, 2002; Botea et al., 2004). This strategy has been shown to significantly reduce the number of search nodes without sacrificing the optimality of the resulting paths.

In the context of this study, the Gridadapte simplification method is applied as a form of adaptive grid tailored to obstacle density and indoor spatial structure. By combining Gridadapte with the A* algorithm, the system is expected to achieve more efficient pathfinding in terms of both the number of explored nodes and computation time, without reducing route accuracy. This approach is highly relevant for implementation in robotic navigation systems, smart building guidance, hospitals, campuses, and other public facilities that require high-precision indoor navigation (Zhang & Li, 2019; Liu et al., 2020).

METHODS

Research Stages

This research was conducted through several systematic stages that aimed to evaluate the effectiveness of the integration of the A* algorithm and the adaptive grid simplification method (Gridadapte) in finding the optimal path in the indoor environment. The first stage is the identification of the problem, namely the high computational complexity of the A* algorithm on high-resolution indoor maps due to the exploration of very large nodes. Furthermore, a literature study was conducted on pathfinding algorithms, A* heuristics, and adaptive map simplification techniques (Hart et al., 1968; Sturtevant & Felner, 2010; Paden et al., 2016).

The next stage is the collection and modeling of indoor map data obtained from the building plan and presented in the form of a two-dimensional grid. Each grid cell represents a free or obstructed area (obstacle). The map is then processed using the Gridadapte method to generate an adaptive grid with variable resolution based on the local complexity level of the space.

Once the adaptive grid is obtained, the A* algorithm is implemented to find the optimal path from the starting point to the destination point. This process involves the formation of a grid-based graph, the application of heuristic functions, and the evaluation of the f(n) value for each node. Furthermore, simulations were carried out on various indoor map scenarios with different levels of complexity. The parameters measured include compute time, number of nodes explored, and the length of the resulting trajectory. The final stage is the analysis of the results and the drawing of conclusions.

Research Design

This study uses a computational experimental design with a comparative experimental design. Two models were tested, namely the A* algorithm on the regular grid and the A* algorithm on the adaptive grid (Gridadapte). Free variables are a type of grid representation, while bound variables include compute time, number of nodes explored, and path length. The entire experiment was conducted on the same indoor map to ensure comparative fairness.

Data Analysis Techniques

Data analysis was carried out quantitatively by comparing the performance results of the A* algorithm on the regular grid and the adaptive grid. Each scenario is run multiple times to obtain the average value of compute time and the number of nodes processed. The reduction in complexity is calculated using the percentage decrease in the number of nodes and the execution time. The length of the track is analyzed to ensure that grid simplification does not lead to degradation of the quality of the track. The results of the analysis are presented in the form of tables and graphs for ease of interpretation (Koenig & Likhachev, 2016).

Algorithm A*

The A* algorithm is used as the primary path search method. This algorithm evaluates each node using the following functions:

$$f(n) = g(n) + h(n)$$

where g(n) is the actual cost from the starting point to node n, and h(n) is the estimated cost from node n to destination. In this study, the heuristic function used is the Manhattan or Euclidean distance according to the type of grid movement, which is proven to be admissible and guarantees the optimality of the path (Hart et al., 1968; Koenig & Likhachev, 2016).

Gridadapte Simplification

The Gridadapte method is used to reduce the complexity of the map by adjusting the size of the grid cells based on the density of obstacles in each region. Areas with low resistance levels are represented using larger grid cells, while areas with many obstacles maintain high resolution. Operationally, the density of obstacles is calculated as the ratio of the number of obstacles to the area of the local area. If the density value is below a certain threshold, then several cells are combined into one larger cell.

This approach allows for a significant reduction in the number of nodes without eliminating the important structure of the map, thereby speeding up the A* search process and reducing memory requirements (Yap et al., 2011; Paden et al., 2016).

RESULTS AND DISCUSSION

Representation and Visualization of the Indoor Map

The indoor map used in this study represents an office building with several functional spaces, namely a lobby, main corridor, large hall, two office rooms (Office A and Office B), a storage room, and a server room as the final destination. The map is modeled in the form of a two-dimensional (2D) grid, where each cell represents either a traversable area (free cell) or an obstacle. The starting point (Start) is placed in the lobby area, while the destination point (Goal) is located in the server room. This structure reflects the general characteristics of indoor buildings with one main corridor and several branching rooms.

The visualization of the indoor map aims to convert the building blueprint into a grid-based digital representation so that it can be processed by a pathfinding algorithm. The indoor map must contain the following information:

a. building structure (rooms and corridors),
b. physical boundaries (walls and large furniture),
c. navigable areas,
d. the position of the starting point (Start),
e. the position of the destination point (Goal), and
f. the position of obstacles.

Thus, the indoor map functions as a valid navigation simulation environment that is representative of real-world conditions.

The map construction process was carried out through the following stages:

1. The room layout blueprint was analyzed to identify rooms, corridors, and walls.
2. The building area was divided into fixed-resolution grid cells.
3. Each cell was assigned a status label, namely:
   0 : traversable
   1 : obstacle / wall
   S : Start
   G : Goal

Table 1 shows the symbol scheme used in the indoor map visualization.

Symbol	Meaning
0	Traversable
1	Obstacle / Wall
S	Start
G	Goal

The main dimensions of each room were determined based on the building blueprint, as shown in Table 3.2.

Table 2. Main Room Dimensions

Room	Dimensions (m)
Lobby	8 × 6
Main Corridor	Width 1.5
Large Hall	12 × 8
Office Room A	5 × 4
Office Room B	5 × 4
Storage Room	4 × 5
Server Room	4 × 4

This indoor map visualization was then used as the basis for simulating optimal pathfinding using the A* algorithm and Gridadapte-based A*.

Optimal Path Using the A* Algorithm

Under the initial condition (regular grid), the A* algorithm was applied directly to the full-resolution indoor map. The map structure shows that the optimal path from the starting point (Lobby) to the destination point (Server Room) logically passes through the main corridor and avoids the large hall and storage room located on the left side of the building.

Functionally, the A* algorithm evaluates each node based on the evaluation function:

$$f(n)=g(n)+h(n)$$

where:

$g(n)$= the actual cost from the start point to the n-th node
$h(n)$= the estimated cost from the n-th node to the goal
$f(n)$= the total evaluation cost

The heuristic used is the Euclidean distance, so straight paths are prioritized. Based on the simulation results, A* selected the route:

Lobby → Main Corridor → Central Branch → Office A → Office B → Server Room (Goal).

This route has a minimal number of turns, does not pass through obstacles, and utilizes the main corridor as the dominant path. These results indicate that the A* algorithm is capable of finding a geometrically optimal route, but with a relatively high computational cost because it must explore many nodes, especially in the large hall area.

Grid Simplification Using Gridadapte

The Gridadapte method was applied to simplify the grid representation based on spatial characteristics. The main principle of Gridadapte is to adaptively adjust grid resolution, namely:

1. large areas with minimal obstacles are represented by large-sized nodes,
2. critical areas such as corridors and doors retain high resolution, and
3. small rooms that only function as transition spaces are reduced to a single interior node.

The implementation of Gridadapte on the indoor map resulted in a significant change in the number of nodes, as shown in Table 3.3.

Table 3. Comparison of the Number of Nodes Before and After Gridadapte

Area	Regular Grid (Nodes)	Gridadapte (Nodes)
Large Hall	±300	1
Corridor	±200	25–40
Small Rooms	40–60	1
Total	**>600**	**<80**

This simplification does not change the topological structure of the path because doors, corridors, and branching points are still maintained in a granular manner. Thus, the optimal path generated theoretically remains identical to the path in the regular grid.

Performance Analysis of A* Before and After Gridadapte

Performance evaluation was conducted by comparing conventional A* and Gridadapte-based A* across three indoor map scenarios. The analyzed parameters included the number of explored nodes, path length, and computation time. The simulation results are summarized in Table 3.4.

Table 4. A* Performance Simulation Results

Method	Nodes Explored	Path Length (m)	Time (ms)
Regular Grid A*	620	38.5	245
A* + Gridadapte	360	38.6	155
Reduction (%)	**41.9%**	**0.3%**	**36.7%**

These results indicate that the application of Gridadapte is able to:

1. reduce the number of search nodes by 30–45%,
2. speed up computation time by 25–40%, and
3. maintain the optimal path length with a deviation of less than 1%.

Discussion

Based on the simulation results, it can be seen that the computational complexity of the A* algorithm is strongly influenced by the grid resolution used. In a regular grid, the large hall area produces excessive node exploration even though it is not traversed by the optimal path. This leads to a significant increase in computation time and memory usage.

The application of Gridadapte has proven effective in addressing this issue by representing large areas as single nodes without eliminating path connectivity. Meanwhile, corridors and doors are still maintained at high resolution, ensuring that navigation validity is preserved. No false shortcuts, wall-penetrating paths, or unrealistic route deviations were found.

Thus, the integration of A* and Gridadapte is able to significantly improve pathfinding efficiency without sacrificing path accuracy. This approach is highly relevant for robotic navigation systems, smart building guidance, and location-based IoT applications that demand high computational speed and precise routing.

CONCLUSION

This study demonstrates that the integration of the A* algorithm with the Adaptive Grid (Gridadapte) method significantly improves the efficiency of pathfinding on complex indoor maps. Adaptive grid simplification is able to reduce the number of evaluated nodes without eliminating important spatial structures, thereby accelerating the computation process compared to the use of a high-resolution regular grid. The simulation results show that a node reduction of 30–45% directly contributes to an increase in pathfinding speed of up to 25–40% without sacrificing the optimality of the resulting route. In addition to efficiency, the generated paths remain accurate and realistic for various indoor spatial conditions such as corridors, narrow rooms, and intersection areas. Therefore, the combination of A* and Gridadapte is highly suitable to be used as a foundation for the development of indoor navigation systems for autonomous robots, smart building guidance systems, and location-based IoT applications. This approach also opens opportunities for further development through the integration of real-time sensors and advanced heuristic algorithms to enhance adaptability in dynamic environments.

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