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Dynamic Processing 2D Maps Method for Robot's Trajectory Planning

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Abstract

Unlike common usage of programmed maps, highly robust maps that mimic reality have rarely been tested for path-planning problems with a variety of search algorithms. Meanwhile, utilizing real-like maps might direct studies toward the image processing field and can be time-consuming. Therefore, this study aims to propose a method to effectively and quickly read and process 2D maps in such a way that search algorithms can recognize them. Simulations are conducted on two maps to show the merit of the proposed method. In all simulations, the proposed method successfully read and processed maps in an average time of 1.5043 seconds. Moreover, the search algorithm, which is a probabilistic roadmap can quickly recognize the maps and plan feasible paths from starting points to target points.

Keywords: image processing, map building, PRM, path planning, search algorithm

1. Introduction

Over the last 3 decades, mobile robots have been effectively utilized in various fields [1-3], including military [4-5], business [6-7], and security settings [8], to carry out vital tasks. Path planning is one of the important tasks for an autonomous mobile robot, which is a technology used to determine a collision-free, efficient, and safe path for a mobile robot or an autonomous vehicle from the starting point to the end terminal in environments filled with various obstacles. Path planning plays an essential role in obstacle avoidance, improving efficiency, accuracy, and increased safety while robots move especially in complex environments [9-11]. For that, path planning has received the attention of numerous scholars and researchers. They tried to develop and enhance a variety of algorithms to address path-planning problems, as outlined in references [12-17]. In most of these works, the algorithms were not tested on maps that simulate reality. Researchers might have avoided this situation because it might increase the workload and consume additional time. Moreover, this situation may be outside their scope of expertise, requiring assistance from specialists in image processing and morphological operations. The researchers evaluated their approaches (algorithms) on programmed maps, such as the one shown in Fig. 1. Usually, programmed maps consist of motifs that do not accurately depict real environments. Accordingly, evaluating the algorithm's performance exclusively through programmed maps is insufficient, not robust, and untrustworthy.

While obstacles of all shapes and sizes, wide and narrow roads, and acute angles of different degrees can be found in real environments. Consequently, more reality-like maps must be utilized to test search algorithms to enhance the testing process and make it more robust and reliable. However, creating a personalized map can be time-consuming, especially when dealing

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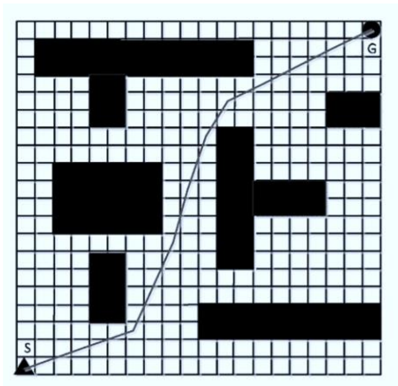
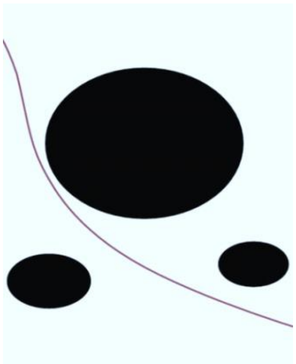
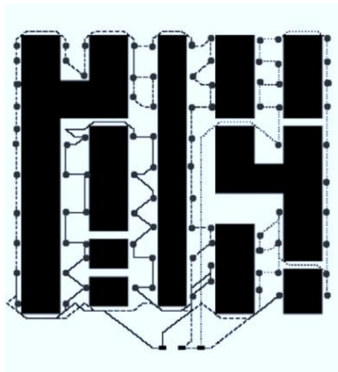
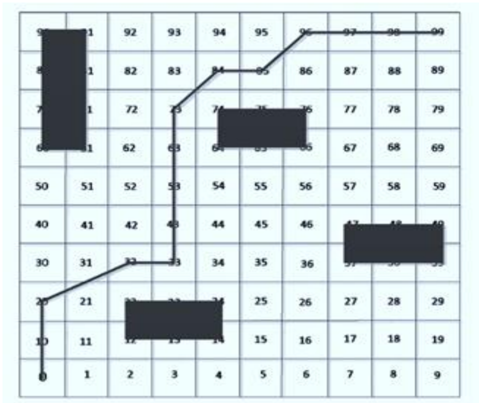
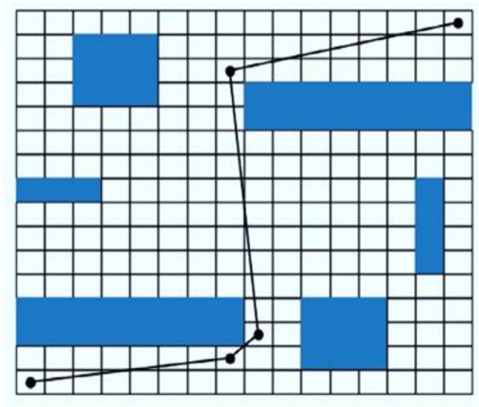
with numerous obstacles of varying sizes and shapes, and may require experts. For that, a simple and fast method is required to read and process map images directly without the need to program them in such a way that ensures variant search algorithms can recognize these maps and plan feasible paths on them.

(a) Mobile robot with a target (b) A smooth path. (c) Task allocation

(d) Mobile robot environment (e) Obstacles in environment

Fig. 1 Pictures illustrating the testing of different algorithms for path planning on programmed maps [12-17]

In this work, an efficient, flexible, and rapid method isproposed to read, and process 2D map images in a manner that variant search algorithms recognize their borders and free areas and their obstacles and plan collision-free paths on them in competitive time and high accuracy. The method mainly depends on image processing and morphological operations. A morphological operation is a technique that analyses the shapes of objects in an image by adding or removing pixels from the image based on the value of other pixels in its vicinity. Boundaries, skeletons, and convex hulls are among the region forms or picture components extracted using this mechanism [18-19].

The remainder of the paper is organized as follows: Section 2 describes the methodology. Section 3 highlights PRM. Section 4 presents the experiments and results. Finally, Section 5 summarizes the conclusions.

2. Methodology

In this section, the proposed method, which reads and analyzes maps that mimic real-world environments, is thoroughly explained. It makes use of morphological operations and image processing. Morphological operations are widely used in image segmentation, object recognition, and feature extraction.

2.1. Image processing and morphological operation

Morphological operations are a mathematical method of manipulating and analyzing the structure of images, and they may be applied to 2D maps. When processing binary or grayscale images, morphological operations come in handy for performing shape analysis, noise reduction, and feature extraction. The two basic morphological operations are erosion and dilation, which, when combined, allow for the completion of extremely complicated tasks. In image processing, the following is a general summary of common morphological operations [18-19]:

- **Dilation**: This effect entails thickening or enlarging the border of an image object. A preset form, like a square or circle, is positioned at each pixel in this process to serve as the structural element. The pixel value is assigned to one if any area of the structuring element overlaps with the object [20-21]. This component can be utilized to draw attention to certain areas, connect disparate parts of an item, and close tiny spaces.

- **Erosion**: This component involves the thinning or shrinking of an object's borders and is the reverse of dilatation. Erosion employs a structuring element like dilation, changing the pixel value to one only when all of the structuring element's components coincide [22]. Erosion helps remove small, isolated details and separate overlapping elements.

- **Opening**: This component consists of a mix of dilatation and erosion. Furthermore, this component is quite good at eliminating noise and small objects. Opening helps break up narrow isthmuses and smooth out object shapes [23]. Additionally, opening efficiently minimizes the sizes of items and removes little structures while maintaining the overall shapes of the larger ones.

- **Closing**: This component relates to the dilatation and erosion processes working together. Closing is a common technique used to plug small holes or breaks in objects. Closing has two applications: it can be used to fix damaged buildings and fill in small depressions [24]. In addition, closure fills in spaces, joins related items, and evens out object shapes.

2.2. Proposed method

The method consists of a set of codes that can be written in any programming language. This method reads 2D map images with a .jpg extension in the first step. Second, this method changes the image to a grayscale image and then to a binary image. Thereafter, this method raises the degree of darkness when necessary. Third, this method determines all objects and their shapes and sizes in the image and encloses their frames based on the morphological operation. Fourth, this method fills all objects that have been identified with black color. In the end, search algorithms, such as PRM, which were utilized in this work, will be able to recognize the map image and seek a path across the free space while avoiding obstacles to reach its destination. The flowchart of the proposed method has been depicted in Fig. 2, while the steps of the proposed method appear in Fig. 3.

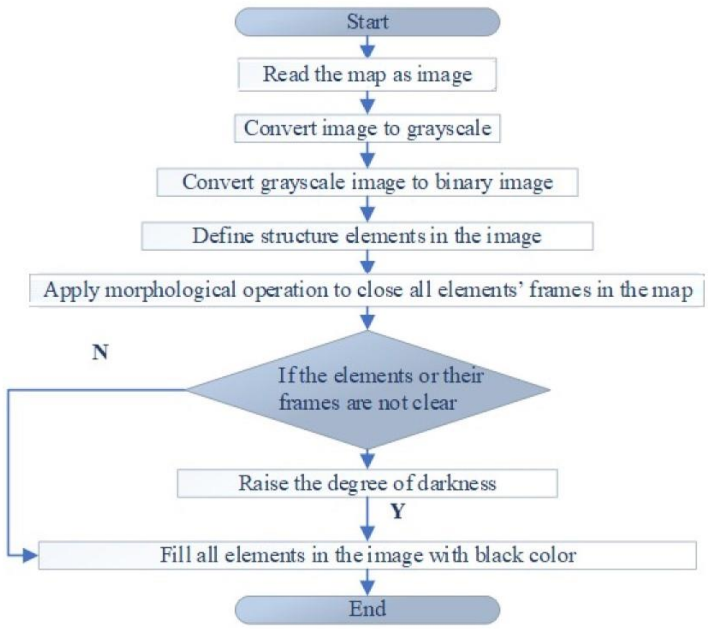


Fig. 2 Proposed method flowchart

Input: 2D image map Output: Recognized map by search algorithm
1.Read the 2D map as image. 2.Convert image to grayscale. 3.Convert grayscale image to binary image. 4.Define all elements inside the image. 5.Apply dilation and erosion (morphological operation). 6.Find the outer boundaries of all elements in the image. 7.Find the inner boundaries of the elements (step 6). 8.Find inner elements inside the inner boundaries for the main elements (step 6). 9.Exclude both inner boundaries and inner elements. 10.With the remaining borders (outer boundaries), create a new binary picture. 11.Programmed features of the binary image's regions. 12.Create a map of binary occupancy. 13.Display the occupancy map.

Fig. 3 The method steps

3. Probabilistic Roadmap Algorithm

To verify the effectiveness of the proposed method for reading 2D map images and processing them in such a way that variant algorithms can recognize their borders and obstacles, a sampling-based technique was utilized for path planning on the processed maps. Sampling-based motion planning is a technique used in the robotic field to plan the path of a robot from a starting point to an endpoint in an obstacle-filled environment.

This technique is based on creating a sample of points in the space of interest and then connecting these points in various ways to form possible paths. Each path is then evaluated to determine whether it can be implemented safely and efficiently.

There are several techniques used in Sampling-based motion planning, such as:

Rapidly-exploring Random Tree (RRT) [25]: This algorithm relies on converting the possible path into a specific path using probability techniques. Its advantages include the ability to deal with complex environments full of obstacles, and determine safe and effective paths. However, on the other hand, it requires a large amount of data and probability techniques in addition to a large amount of time and effort for analysis and evaluation.

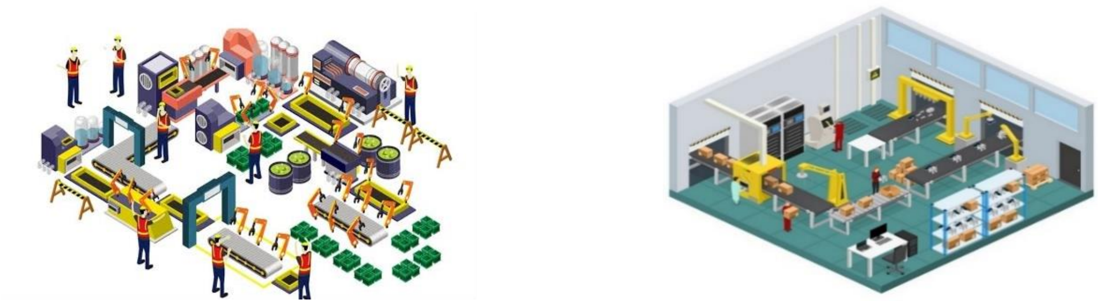
Input: Identified map and PRM Output: Feasible path
1.Initialize an empty graph G 2.In the configuration space, generate random samples and look for instances where they collide with obstacles. 3.Add collision-free samples to the graph G 4.Connect nearby samples in G using local planners and check for collisions 5.Add collision-free edges to the graph G 6.Repeat steps 2-5 until enough samples and connections are added to G 7.Use a path planning algorithm (e.g., A* or Dijkstra's) to find a path from the start to the goal using the graph G

Fig. 4 PRM steps

Probabilistic Roadmap (PRM) Recent path planning research has paid close attention to the PRM [26-27] because of its ease of use and capacity to navigate high-dimensional configuration spaces. The three major steps of the PRM are as follows: (1) creating random nodes in the free configuration space; (2) connecting these nodes to form a single graph by combining edges that cross the free space; and (3) analyzing the graph to find the shortest path between the start and goal nodes [28]. Fig. 4 lists the steps of PRM.

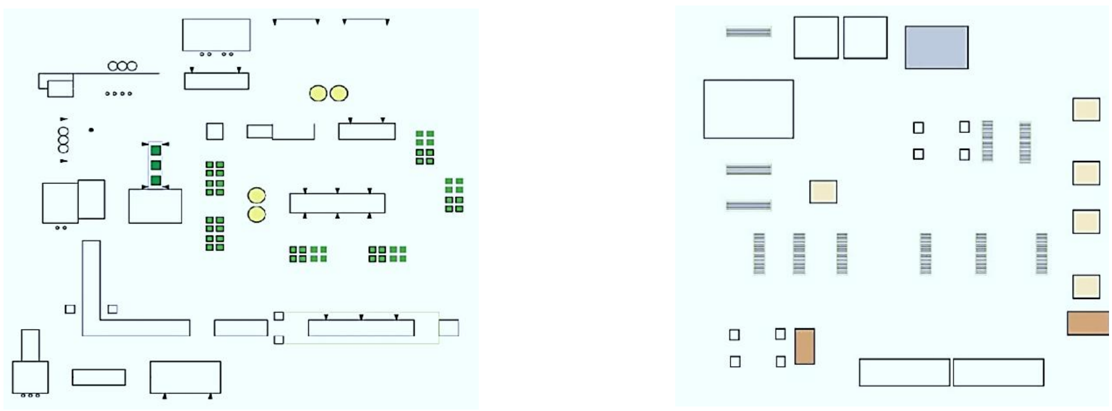
4. Experiments and Results

To demonstrate the effectiveness of the proposed method, several simulation experiments have been conducted. Two real-like map images with different sizes and degrees of complexity (installed from the internet) have been utilized to prove the scalability and flexibility of the proposed method as shown in Fig. 5(a) for the complex map and Fig. 5(b) for the simple map. An initialization stage was conducted where the two map images were drawn with AutoCAD, and the outcomes were saved as images with a.jpg extension, as shown in Figs. 6(a) and (b).



(a) Complex map (b) Simple map

Fig. 5 Original images



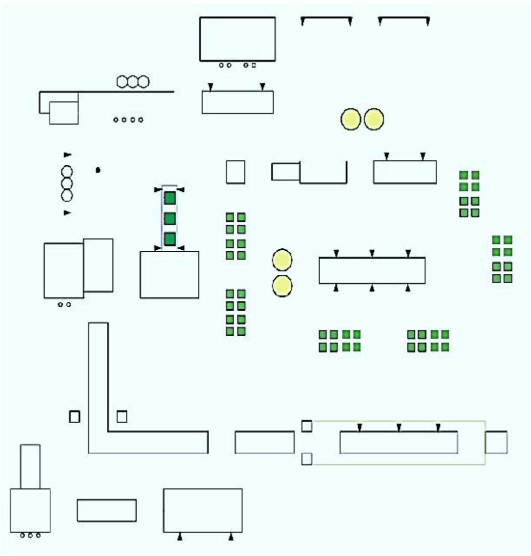
(a) Complex map (b) Simple map

Fig. 6 Two maps' images drawn by AutoCAD in the initialization stage

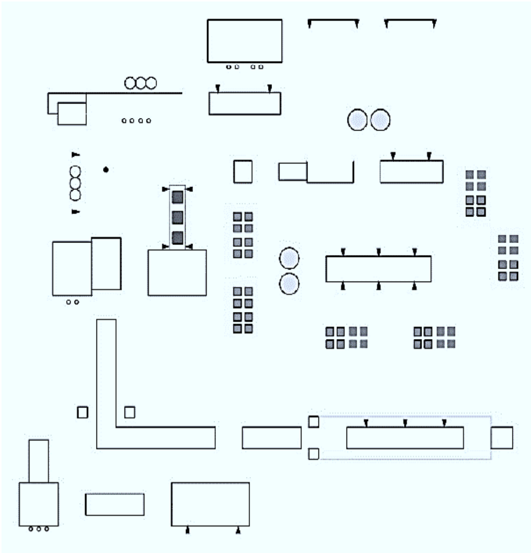
Once the proposed method has been executed, the map image has been processed and constructed in a manner that makes it recognizable for search algorithms by several steps, as shown in Fig. 7 for the complex map and Fig. 8 for the simple map. The PRM algorithm has been applied to the processed map images for path planning to test the proposed method. Two scenarios have been chosen: in the first scenario, path planning for a single robot with a single start point and a single target point; in the second scenario, path planning for three robots, each of which has its own start point and target point on both maps. Table 1 lists the PRM parameters used for the two maps and both scenarios.

Table 1 PRM Parameters

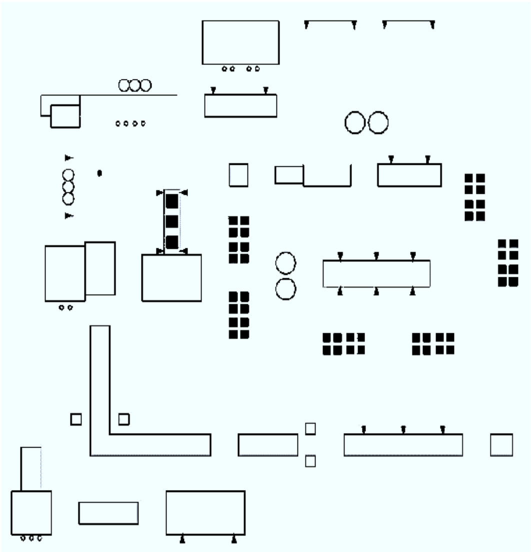
No.	Parameter	Value
1	Number of nodes	1000
2	Number of lines	100



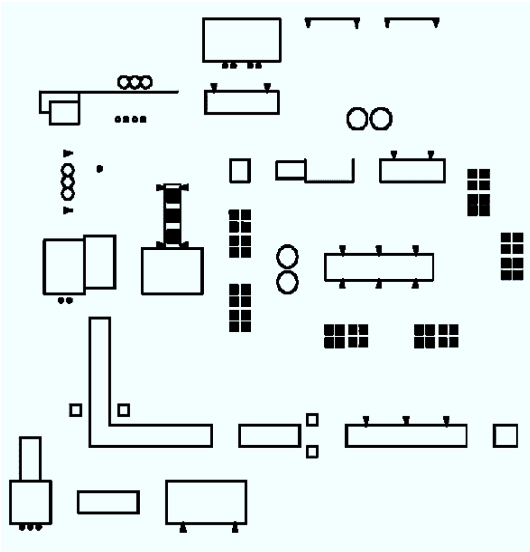
(a) Reading the map's image



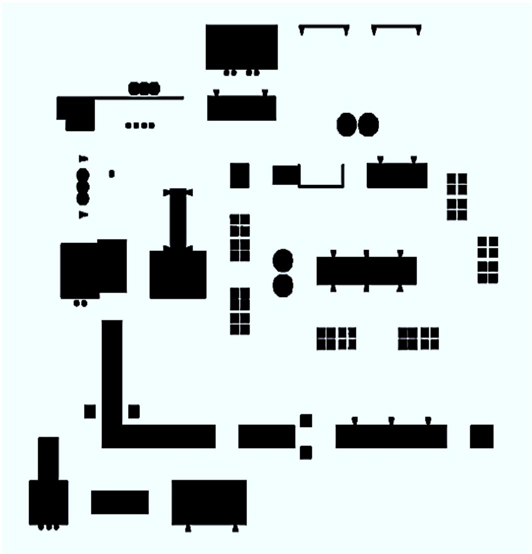
(b) Converting the image to grayscale



(c) Applying morphological operations to find boundaries of the image and all its objects

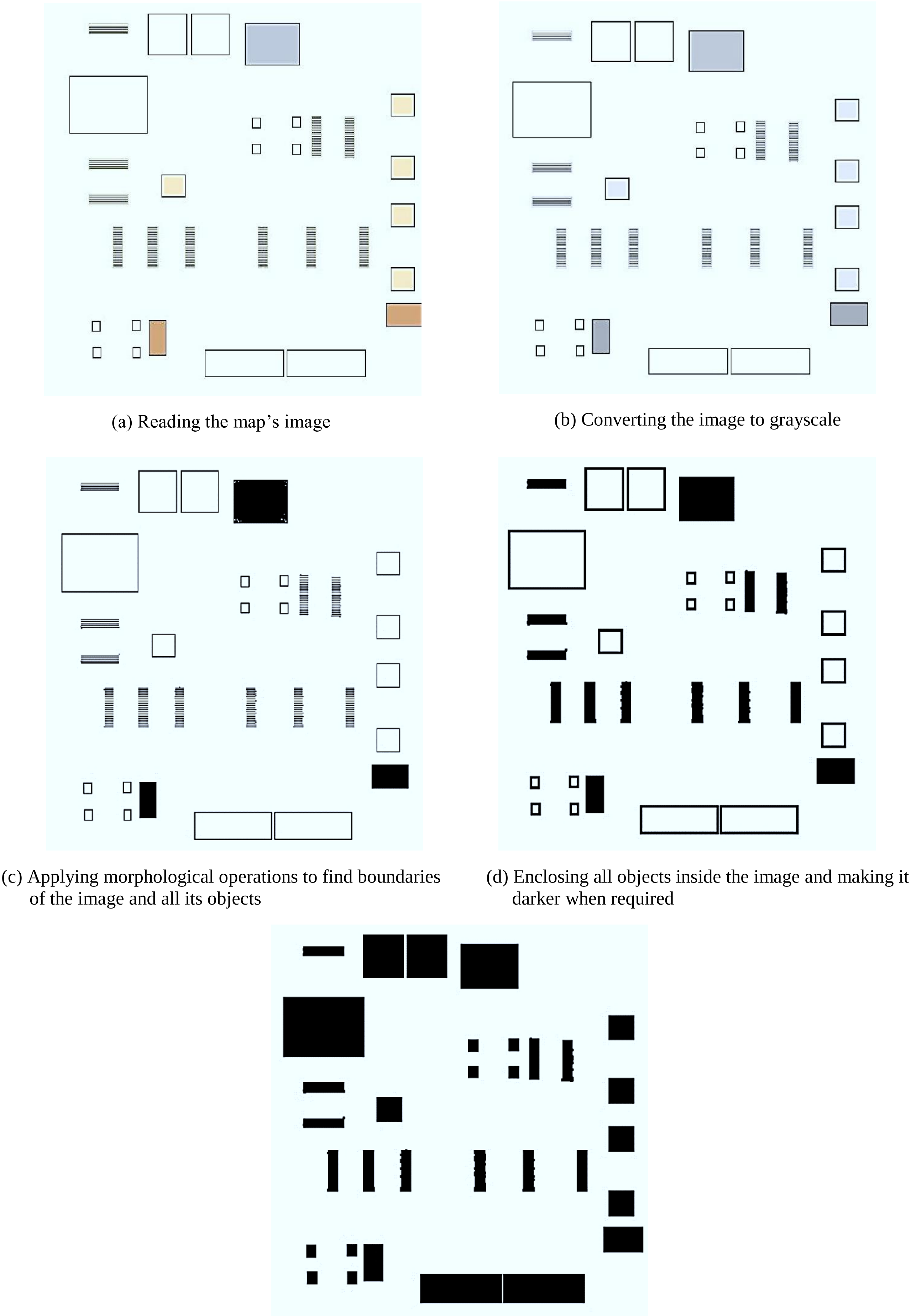


(d) Enclosing all objects inside the image and making it darker when required



(e) Filling all objects with black to ensure that they could be identified as obstacles by search algorithms

Fig. 7 The steps of processing the image of a complex map



(a) Reading the map's image

(b) Converting the image to grayscale

(c) Applying morphological operations to find boundaries of the image and all its objects

(d) Enclosing all objects inside the image and making it darker when required

(e) Filling all objects with black to ensure that they could be identified as obstacles by search algorithms

Fig. 8 The steps of processing the image of a simple map

In the first scenario, PRM has been applied to the complex map in Fig. 9 for path planning between the starting point [2, 1] and target point [500, 500] and on the simple map in Fig. 10 between the starting point [2, 1] and target point [400, 350]. In the second scenario, PRM has been applied to the complex map in Fig. 11 for planning three paths, each of which has a different start and target, and on the simple map in Fig. 12.

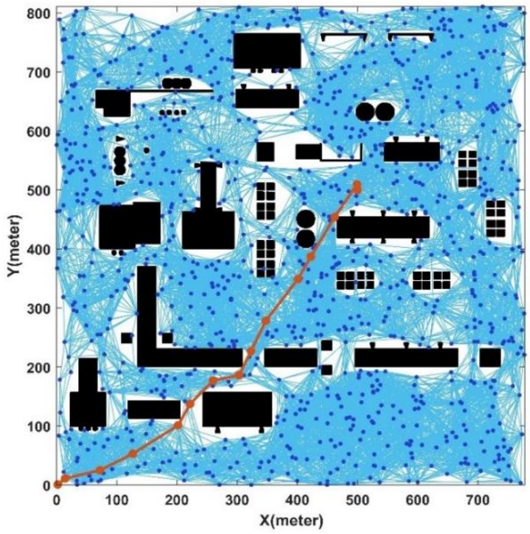


Fig. 9 Single path with start point [2, 1] and target point [500, 500] on the complex map

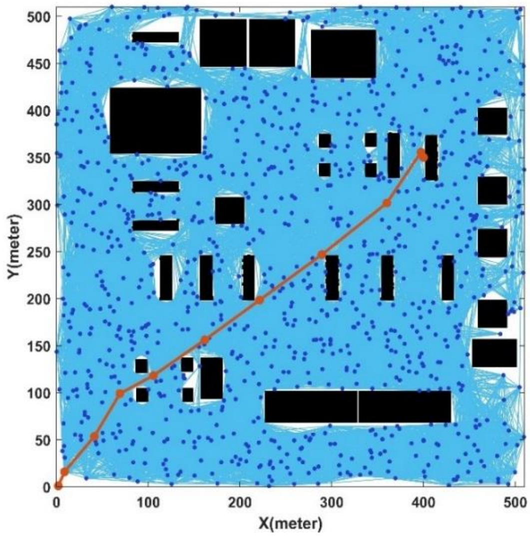


Fig. 10 Single path with start point [2, 1] and target point [400, 350] on the simple map

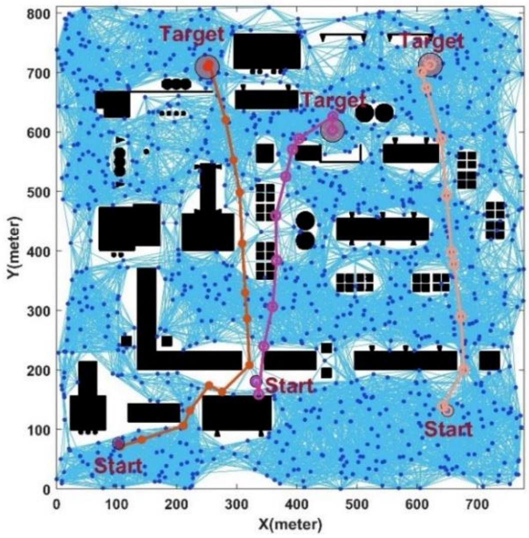


Fig. 11 Three paths with different start points and target points on the complex map

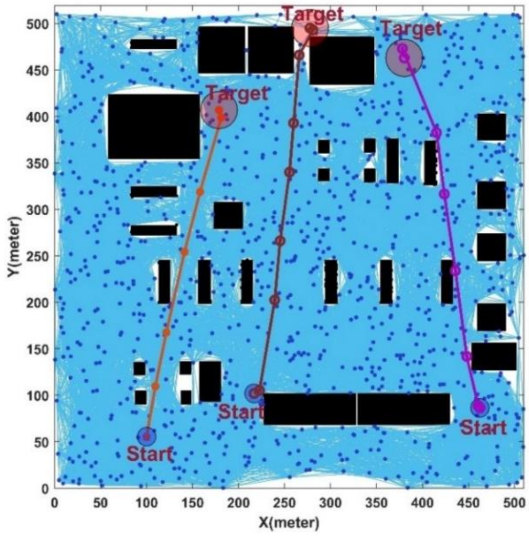


Fig. 12 Three paths with different start points and target points on the simple map

In all scenarios, the PRM algorithm recognized the boundaries and inside objects of the two maps and determined the shortest paths between the start and the endpoints while avoiding collisions with obstacles, as shown in Figs. 7, 8, 9, and 10. The two scenarios for each map have been run 20 times to achieve robust and trusted results, and the averages were calculated. The average running time of processing the two map images and the average PRM algorithm running time for both maps in the two scenarios are presented in Table 2.

Table 2 Time Compression.

Map Method		Complex	Simple
First scenario (single target)	Map processing time (s)	1.5125	1.4519
	PRM running time (s)	1.8979	1.8576
	Total time (s)	3.4104	3.3095
Second scenario (three targets)	Map processing time (s)	1.5819	1.4712
	PRM running time (s)	25.2608	24.1491
	Total time (s)	26.8427	25.6203

The time required for a map's image processing is almost the same for the two maps, despite the maps' differences in sizes and degrees of complexity. In contrast to grid-based decomposition, which is usually used to represent the environment or map [29-30]. The processing speed of this method is affected by the degree of accuracy, the size of the map, and its complexity, which in turn greatly affects the time required to process maps.

The simulation results demonstrated the ability of the proposed method to process any realistic map with any size and degree of complexity with very high accuracy and an average time of 1.5043 seconds, which makes this method suitable and practical in real-world applications. The results highlight the method's capability to integrate with the probabilistic roadmap algorithm, ensuring reliable path planning from start to target points.

5. Conclusions

In this article, a simple, fast, and effective method has been proposed to read and process 2D map images, enable various search algorithms to recognize their borders and obstacles, and plan a collision-free path for a mobile robot. The proposed method was assessed using two realistic maps that varied in terms of size and complexity, and the probabilistic roadmap algorithm for path planning on the two maps to demonstrate its feasibility and efficacy. The results of the simulation experiments revealed the effectiveness of the suggested method in reading and processing the maps in an average time of 1.5043 seconds for both maps, which is particularly valuable for real-time applications. Furthermore, the PRM algorithm quickly identified borders, obstacles, and free areas of the two maps and successfully planned a feasible path between starting points and target points. This ability to process realistic maps efficiently ensures that the proposed method can be readily applied to real-world scenarios. Concerning future work, more experiments need to be done on various environments and in variant applications in areas such as autonomous vehicles, drones, and robotic systems.

Conflicts of Interest

The authors declare no conflict of interest.

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