Rescue Boat Path Planning in Flooded Urban Environments

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Abstract*—Mapping and path planning in disaster scenarios is an area that has benefited from aerial imaging and unmanned aerial (UAV) and surface vehicles (USV). Nowadays, there are many application areas of UAV and USV which consist of environmental monitoring, victim recovery and river mapping in the purpose of rescue operations. There are many challenges for flood rescue operations with existing systems where the time response is critical. The environment is completely changing under flood conditions and it causes a dangerous environment for victims and rescue operators. Rescue boats are widely used for searching and rescuing the victims in the flooded areas. However, rescue boats have a limited view while searching and rescuing the victims. By using UAVs, an aerial image can be taken off the flooded environment and this aerial image can provide global information such as the location of victims and landmarks. The rescue operations can be organized based on a generated flood environment map by using this global information. Here we propose a ground map generation and path planning algorithms, which makes use of aerial imaging provided by a UAV in flooded urban environments. Based on the generated ground map, we used the concept of mobile robot path planning to represent our proposed approach in rescue boat path planning. In this purpose, A*, GA and PRM path planning algorithms are used and analyzed to find near-optimal paths for rescue boat between initial and target locations. Experiments are performed to evaluate the performance of the system algorithms to find out the most suitable algorithm in flooded urban environments.

***Keywords*—path planning, unmanned aerial vehicle, map building, flood rescue operations, rescue boat**

I. Introduction

Natural disasters have serious impacts on human lives in terms of both losses of life and property. One of nature's most turbulent years was 1998. Floods wreaked havoc in Asia, Europe, North America and South America. Many people suffered from these heavy floods which had cost great casualties and losses. USVs and UAVs have seen recent use in helping with various rescue operations. There are many application areas of USVs which consist of environmental monitoring [1], hazardous spill detection [2], victim recovery [3], river mapping [4], surveillance of shipwreck survivors at sea [5] and object recovery on the sea surface [6]. In Hurricane Wilma, 2005, UAVs and USVs were used for the first time as a cooperation system for the recovery phase of disaster management by detecting damage to seawalls and piers, locating submerged debris and determining safe lanes for sea navigation [2]. There are many challenges for flood rescue operations with existing systems where the time response is critical. The environment is completely changing under flood conditions, especially when some chemical substances spill into the flood areas and it causes a dangerous environment for victims and as well as rescue operators. Rescue boats are widely used for searching and rescuing the victims in the flooded areas. However, rescue boats have a limited view while searching and rescuing the victims. By using UAVs, an aerial image can be taken off the flooded environment and this aerial image can provide global information such as the location of victims and landmarks. The rescue operations can be organized based on a generated flood environment map by using this global information.

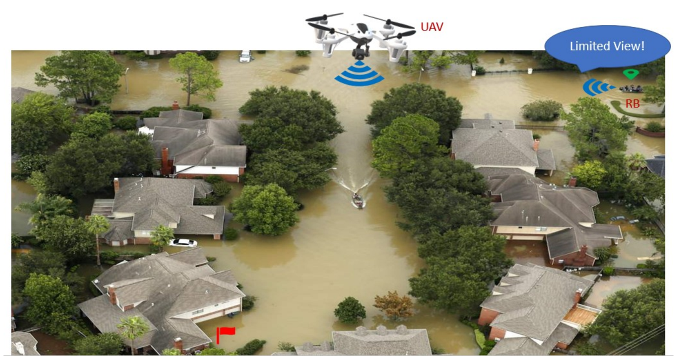


Fig. 1. Aerial view of a flooded environment. The rescue boat has a limited view to reaching the destination point. By using a UAV, the global information of the flooded environment can be used to model a ground for rescue boat path planning.

Fig. 1 displays a typical urban flood scenario where the aerial image can provide global information for rescue boat path planning. This research mainly aims at a map generation of the flooded area by using global information from UAV for rescue boat path planning. To the authors' knowledge, this is the first known study of rescue boat path planning by using aerial imaging in flooded urban environments.

Main system processes

In this research, we consider a flood rescue application where the main goal is to build a ground map and plan near-optimal paths for a rescue boat. The main system processes of this research are as follows:

1) Using the UAV, a ground image is obtained from above, and then processed to segment obstacles. The segmentation of the obstacles is done by using image processing algorithms such as image denoising and obstacle recognition techniques. This creates a ground map based on the locations of obstacles and the feasible paths.
2) Based on the generated ground map, we analyzed different path planning algorithms such as A*, GA and PRM to find near-optimal paths for the rescue boat.
3) Map building process is performed by using OpenCV tools and path planning algorithms are performed by MATLAB generated codes to validate the performance of the proposed approach.

The remainder of this paper is organized as follows. Section II discusses previous work. Section III describes our system design and explains its main components. Section IV provides the experimental results of our system algorithms along with a performance analysis. Section V concludes the paper.

II. Related Works

Using unmanned vehicles in rescue operations is not a brand new topic. Deng et al. [7] studied automatic ground map building and path planning in a UAV/UGV cooperative system for ground disaster rescue operations. More recently, Lakas et al. [8] introduced a framework for cooperative mission planning where a UAV and a UGV work cooperatively for a rescue task. Zhang et al. [9] introduced a new system which consists of a USV, a UAV, and a take-off and landing system. In 2017, Xiao et al. [10] present the first known implementation of a small UAV visually navigating a USV to rescue problems by extending the rescuers victims in an efficient manner.

In the field of map building, many computer vision algorithms have been developed in the literature. Costea et al. [11] proposed a system for geo-localization from aerial images in the absence of GPS information. This research includes the development of computer vision algorithms for the recognition of road, intersections, buildings and landmarks. Zhou et al. [12] present an efficient road detection and tracking framework in UAV videos is proposed. Li et al. [7] proposed a ground map construction by the aerial image from UAV which was processed with image denoising, correction and obstacle detection techniques in UAV/UGV cooperation system. A survey on computer-vision algorithms for obstacle detection in aerial images which are produced by UAV is analyzed in [13]. More recently, Gunasekaran et al. proposed a map generation in a static unknown environment by using a mobile robot [14].

In the field of path planning, it has become one of the fundamental study areas in unmanned vehicle systems. Cheng et al. [15] proposed an improved hierarchical A* algorithm to solve parking path planning issues of a large park. In [16], a heuristic-based method is proposed to search the feasible initial path efficiently to solve the problem of dynamic environments. Li et al. [7] proposed a hybrid path planning method which consisted of genetic algorithm and local rolling optimization methods. Kurdi et al. [17] presented probabilistic roadmap (PRM) path planning method for UGV by using digital map of UAV/UGV cooperative system. However, the existing UAV and USV cooperation systems have not had much intention than UAV/UGV cooperation systems in the research area of path planning. Line-of-sight control is the most widely used control strategy for path planning of UAV/USV system. Nizami et al. [18] presented the first known implementation of rescue boat path planning by using A*, Dijkstra and Breadth-first algorithms in 2012. However, this proposed system has some limitations. For example, the environment is defined as a marine with fully certain islands but a flooded urban environment is not tested with the proposed approach. Therefore, further study is needed to improve the performance of path planning in complex scenarios.

III. System Description

In this paper, we address the problem of mapping an unknown flood environment by recognizing obstacles and roads in the aerial images which are captured by a UAV. We consider a typical flood disaster scenario where the rescue boat can plan optimal trajectories by using an aerial view of the flooded environment for reaching the victims in the most efficient manner.

Fig. 2 shows the general system design of the proposed approach. When the UAV captures the aerial image, the first step is image denoising to recover the aerial image to remove present noise in the aerial image because the noise will affect the performance of the following steps. After image denoising, obstacles are extracted and a ground map model is generated. Based on the generated ground map, the rescue boat can plan a path to reach destination points. In path planning, we applied A*, GA and PRM path planning algorithms to find near-optimal paths on the generated ground map. These processes are detailed in the following sections.

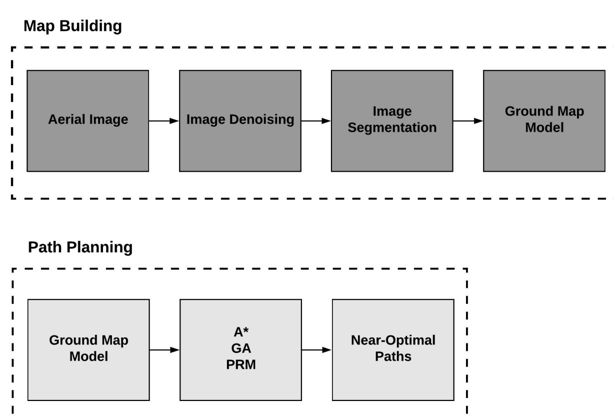


Fig. 2. General system design.

A. Map Building

Map building is the foundation of path planning, which is critical for a rescue boat to reach its destinations accurately. For the rescue boat, the map will be changed dynamically when the vehicle is moving. By contrast, for a UAV, the ground environmental information is nearly unchanging. Therefore, after the UAV has collected the aerial image, image processing is necessary to extract obstacles for building a ground map. Fig. 3 shows the general process of image processing for map building. The process of building the ground map by using image processing algorithms illustrated in the following main steps:

1) Image Denoising: In the step of image denoising, Gaussian filtering technique is applied to blur images and filter possible noise in the aerial image. The results in a blur that preserves boundaries and edges better than the original image.

2) Image Segmentation: In this step, the filtered image is converted to grayscale and then canny edge detection technique is applied to extract contours accurately by transforming the grayscale image to binary image. After extracting the contours, erosion and dilation morphological operation techniques are applied to model a ground map by using square structuring elements.

B. Path Planning

In this section, we utilize the generated maps and introduce path planning algorithms. In flood rescue application, one critical issue is making sure rescue vehicles will not collide with the obstacles in the path. In our system, the rescue boat should avoid collision with the obstacles while performing their tasks. In order to solve the obstacle avoidance problem, we analyzed A*, GA and PRM path planning to find collision-free paths.

1) A:* A* path planning algorithm is a standard graph search based technique. The A* algorithm takes a graph as input and explores all the regions to find the shortest path from the initial point to the destination points in the explored regions [19]. The A* algorithm is heuristic based and works hierarchically which means that all the near regions are explored before the further ones while the exploration is also biased towards the regions closer to the destination points [20].

In general, a graph consists of vertices and edges. Each pixel of the map is taken as a vertex in this algorithm and each vertex has a number of connections which act as edges. In Fig. 4, the possible connections are given for any general position of the vehicle which is represented as a connection matrix as shown. In the connection matrix, the current position of the vehicle is marked as ’2’. There needs to be only one current position of the robot which means that only one ’2’ should be in the matrix. All possible moves are represented by 1 and all impossible moves are represented by 0.

The connection matrix is an input parameter of the A* algorithm and we can create our own matrices to test the efficiency of the system. There are three typical connection matrices which are shown in Fig. 5 [21]. Fig. 5(a) only allows the vehicle to take linear moves such as up, down, left and right. Fig. 5(b) allows the vehicle to take four different diagonal moves together with the four linear moves. Fig. 5(c) allows the vehicle to make more moves while adding connections between the diagonal moves. Allowing more movements for the vehicle by adding more connections can help to generate a better path. However, adding more connections may result in excessive computation time. Another design specification of the algorithm is a cost function. The cost function consists of heuristic and historic functions. The heuristic function,

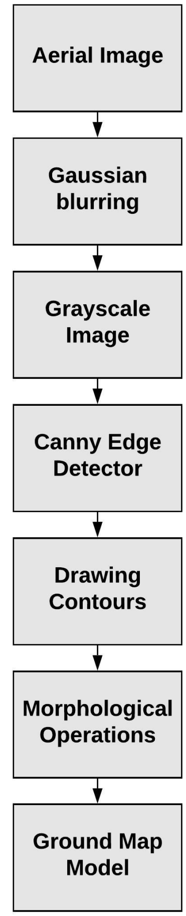


Fig. 3. Ground map model building process.

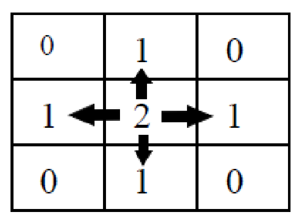


Fig. 4. A* algorithm connection matrix.

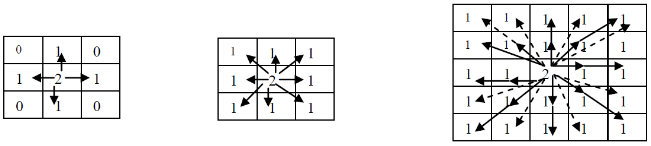


Fig. 5. A* algorithm connection matrices.

H, stores the weights of the edges, which are taken as the Euclidean distance between the connecting points, as shown in equation (1):

$$H(x_i, y_i, x_j, y_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

The historic nearness function, N, which determines the nearness of the point to the goal while finding the Euclidean distance between a point and the goal, as shown in equation (2):

$$N(x_i, y_i, G_{x_j}, G_{y_j}) = \sqrt{(x_i - G_{x_j})^2 + (y_i - G_{y_j})^2} \quad (2)$$

The cost function, C, is summation of heuristic and historic functions which is show in equation (3):

$$C = H(x_i, y_i, x_j, y_j) + N(x_i, y_i, G_{x_j}, G_{y_j}) \quad (3)$$

2) GA: GA is a meta-heuristic search algorithm which applies Darwin's principle of natural selection to model path planning problems. The goal is to find a solution path (sequence of waypoints) that minimizes the distance of the path while remaining collision-free. A collision-free path is called a feasible solution and the feasible solution with minimum distance is an optimal solution for the path planning problem. GA was used in the research to find solutions paths as a waypoint sequence. Waypoints are coordinate values in the GA search space. The solution is stored in an array of size 2 times the number of waypoints where each pair of array values is waypoint (equation 4).

$$path = ((X1, Y1), (X2, Y2), ..., (Xn, Yn)) \quad (4)$$

In order to make some path from this set of waypoints, we start from the source and connect it to the first waypoint by a straight line. The first waypoint is connected to the second waypoint by a straight line, and so on. In the end, the last waypoint is connected to the goal.

Fitness function

In problem modeling, we need a fitness function and specification of variables of that fitness function. Distance minimization is computed using the Euclidean distance (equation 5) between each pair of waypoints to measure the paths length (equation 6) is sub-path between adjacent waypoints.

$$D(x_i, y_i, x_j, y_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (5)$$

$$Path_D = \sum_{i=1}^{n-1} D(< x_i, y_i >, < x_{i+1}, y_{i+1} >) \quad (6)$$

Collision avoidance is implemented by having an obstacle presence along a path. This impacts the individual's fitness value. The fitness function includes a component for penalizing infeasible solutions in the search space. The Penalty (P) is set to an arbitrarily high value. In our problem scenarios, we have set the penalty to 1000000. The S_{INF} is defined as the length of the infeasible portion on the map. In this approach, the infeasible portion is identified based on the color of an obstacle which is lying between each pair of waypoints. The binary image has pixels which are filled in black. The black pixels are the evidence of the presence of obstacles and it is infeasible for the rescue boat to move over it. Thus a heavy penalty (P) is added to infeasible segments S_{INF} as shown in equation 7.

The fitness function is comprised of the distance minimization and obstacle avoidance functions as shown in equation 8.

$$Path_O = S_{INF} * P \quad (7)$$

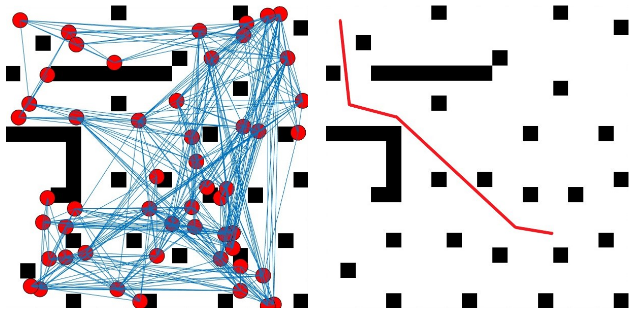
$$Fitness_{path} = Path_D + Path_O \quad (8)$$

The locations of each of these fixed number of points in x and y coordinates are the optimization variables. The variable bounds are such that the waypoint lies inside the map (lower bound 1 and upper bound as the length/width of the map for the X/Y axis). All points put one by one makes the genetic individual used for optimization.

Each waypoint in the path marks a waypoint of turn. The total number of points is an algorithm parameter and should be equal to the maximum number of turns a robot is expected to make in the robot map. Setting this number too high would result in very large computational requirements. If the algorithm is not allowed a large computational time, random results may be the output. Setting a large value in simple scenarios will result in useless turns and hence a high path length. A too small value of the parameter may not give enough flexibility to the algorithm to model the optimal path, thus resulting in collision-prone paths.

3) PRM: Probabilistic roadmap path planning algorithm is a sampling-based path planning technique which consists of two stages: a construction and a query stage. The goal of the construction stage is to randomly draw a graph (roadmap) across the environment. The roadmap is a graph which consists of vertices and edges. All edges and vertices of the roadmap should be collision-free so that the rescue boat can use the roadmap for their task planning. The PRM selects a number of random nodes in the work-space as the vertices where the nodes must not lie inside of the obstacles. Then, the algorithm connects all pairs of randomly selected vertices. If any two vertices can be connected by a straight line, the straight line becomes an edge which is shown in Fig. 6.

The goal of the query stage is to use the roadmap which is developed earlier for finding the shortest path for the rescue boat. The distance between each node and the position of the nodes should be considered to find the shortest path. Therefore, a cost function which is the same as in the A* algorithm (see equation (1), equation (2) and equation (3)) should be applied in this purpose.



(a) (b)

Fig. 6. (a) Roadmap (b) Path Derived

IV. Experimental Results

In this section, we present the experimental results to show the effectiveness of the proposed algorithms. In our experiment, we used an aerial image which is taken from Houston in Hurricane Harvey (2017) [22]. Then, the image is segmented by using proposed image processing techniques to model a ground map. Fig. 7 shows the general process of a ground map model generation in the flooded urban environment image. After building the ground map, path planning algorithms are applied to find near-optimal paths for rescue boat between source and destination points. The parameters used for each algorithm in our experiments are shown in Table I. The starting point is defined as (50, 1100) and the destination point is defined as (2300, 1100) in x and y coordinates for all the algorithms. The planning paths are indicated by the blue curve.

TABLE I
Algorithm Parameters

Algorithm	Source(x,y)	Destination(x,y)
A*	(50, 1100)	(2300, 1100)
GA	(50, 1100)	(2300, 1100)
PRM	(50, 1100)	(2300, 1100)

In A* path planning algorithm experiments, we analyzed three connection matrix (see Fig. 4 (a), (b) and (c)) which are shown in Fig. 8 (a), (b) and (c) respectively in the generated ground map. According to the path planning results in Table II, increasing the flexibility of the movement in the connection matrix can produce a shorter path and less computation time.

TABLE II
A* Algorithm Comparisons

Connection Matrix	Path Length(m)	Computation time(sec)
1	2604	288
2	2432	277
3	2386	209

In GA path planning experiments, we analyzed three different paths which are generated with the different number of waypoints which are shown in Fig. 12 (a), (b) and (c) respectively. In these experiments, the same population size and number of iterations are applied as input parameters. In

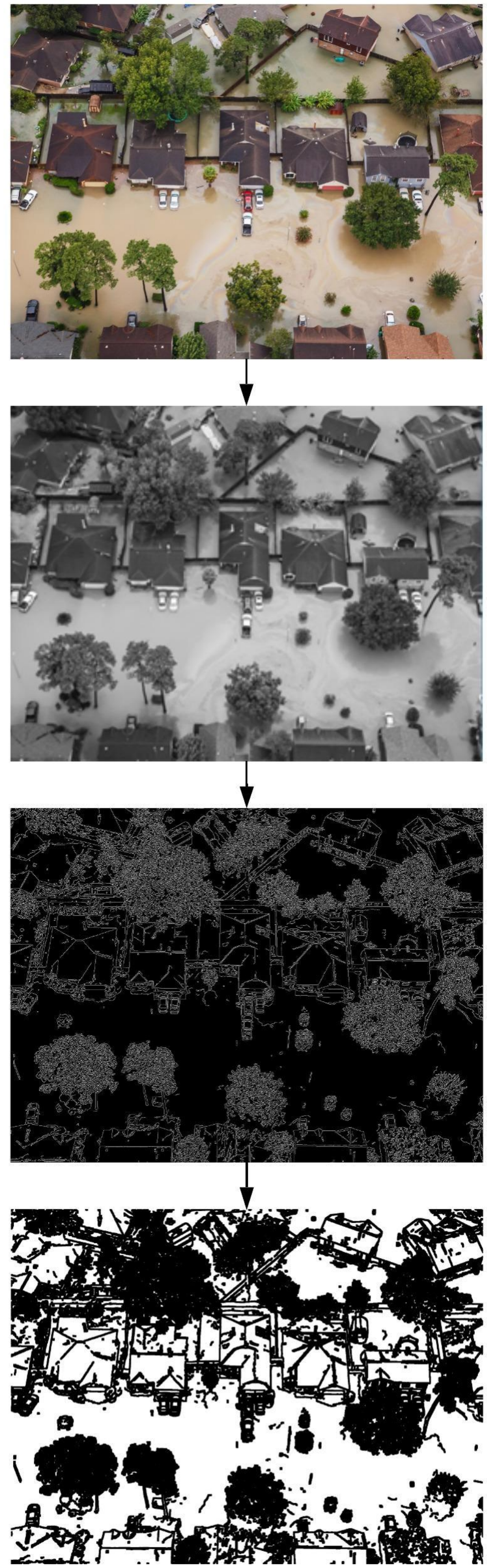
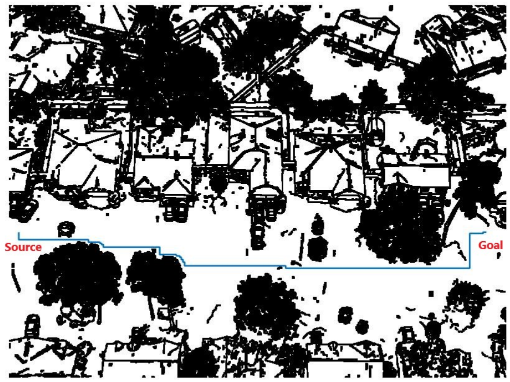
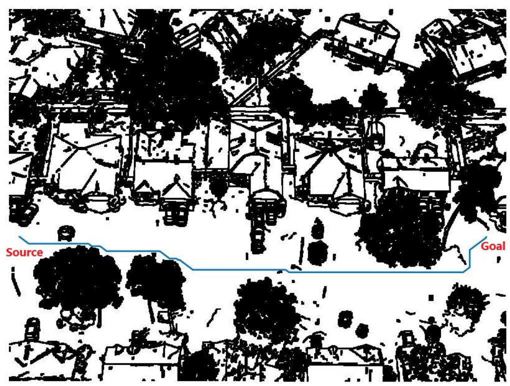


Fig. 7. A ground map model generation.



(a)



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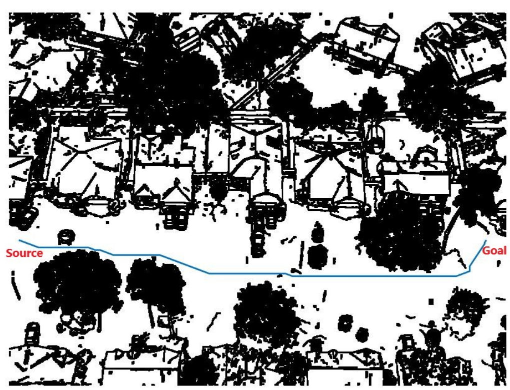


(c)

Fig. 8. (a) A* with Connection Matrix 1 (b) A* with Connection Matrix 2 (c) A* with Connection Matrix 3

addition, the fitness function results vs. the number of generations of these three paths are shown in Fig. 10. According to the results in Table III, increasing the number of waypoints can produce larger path and more computation time.

TABLE III
GA ALGORITHM COMPARISONS

Num. of waypoints	Pop. size	Num. of iterations	Path Length(m)	Comp. time(sec)
3	80	60	2522	98
4	80	60	2730	106
5	80	60	2821	138

In PRM path planning experiments, we analyzed three different paths which are generated with the different number of nodes. Firstly, nodes are generated randomly into the ground map and the possible connection between each node are generated to produce roadmaps in the construction stage which are shown in Fig. 11. Then, near-optimal paths are generated in the query stage which is shown in Fig. 12. According to the results in Table IV, increasing the number of nodes can produce a shorter path and but more computation time.

TABLE IV
PRM ALGORITHM COMPARISONS

Number of nodes	Path Length(m)	Computation time(sec)
100	2427	17
150	2383	27
200	2360	35

V. CONCLUSIONS AND FUTURE WORK

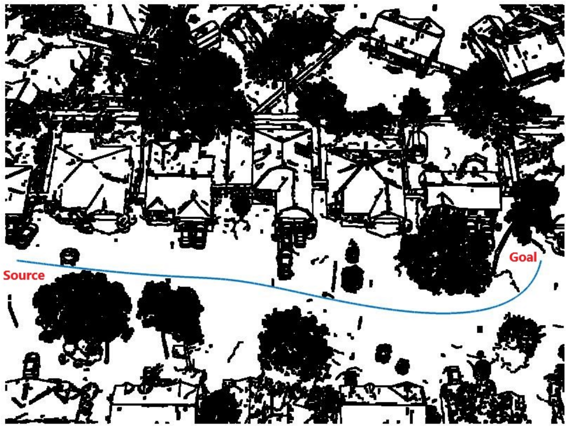
In this research, we proposed a flood rescue application where the main goal was building a ground map and plan near-optimal paths for a rescue boat in a flooded urban environment. Map building and path planning algorithms are expected to greatly enhance the function of the rescue boat to handle flood rescue operations.

A* path planning algorithm is simple and efficient, and increasing the flexibility of the movement in the connection matrix can produce a shorter path and less computation time. However, A* star algorithm is too slow in complex scenes.

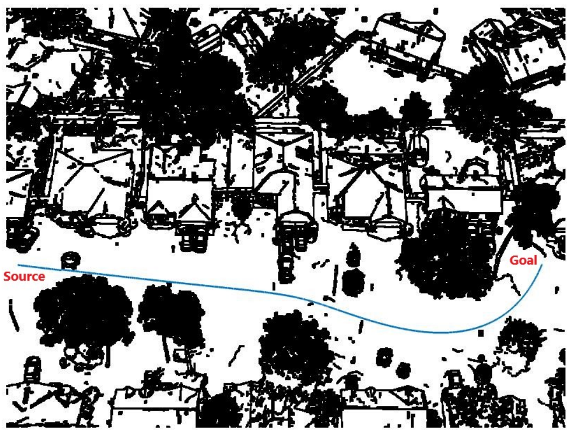
GA path planning algorithm is easy to understand and complete method. However, increasing the number of waypoints, population size and number of iterations can produce larger path and more computation time.

PRM path planning algorithm is simple and fast. However, computation time increases with the number of nodes. According to the path planning algorithm results, PRM path planning algorithm gives a shorter path and better computation time than A* and GA algorithms.

The proposed research does not address all issues, but it is a step towards enhanced flood rescue operations. Rather than focus on hardware building, the research was the focus on testing system algorithms. Our next step will focus on the real world application to test system algorithms by using UAV/RB cooperative system.



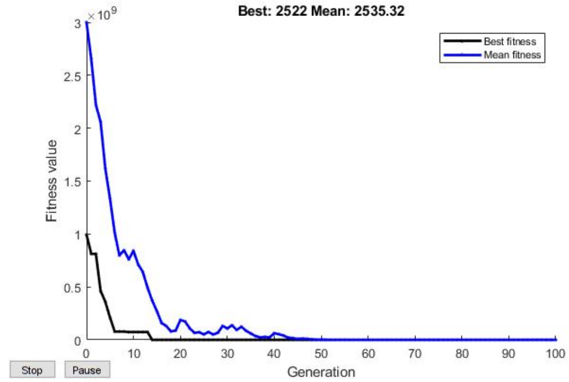
(a)



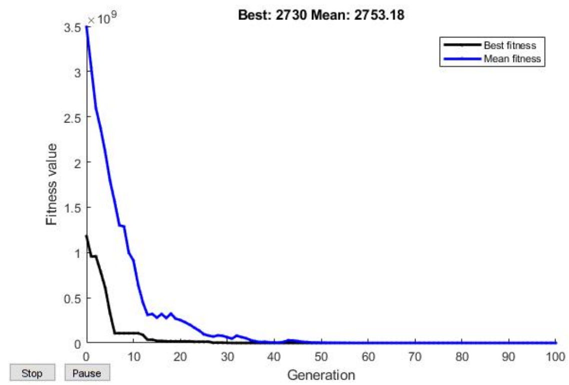
(b)

(c)

Fig. 9. (a) GA path with 3 waypoints (b) GA path with 4 waypoints (c) GA path with 5 waypoints



(a)



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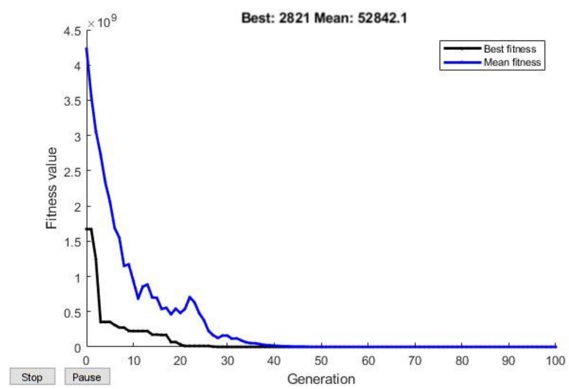

(c)

Fig. 10. (a) Fitness function graph with 3 waypoints (b) Fitness function graph with 4 waypoints (c) Fitness function graph with 5 waypoints

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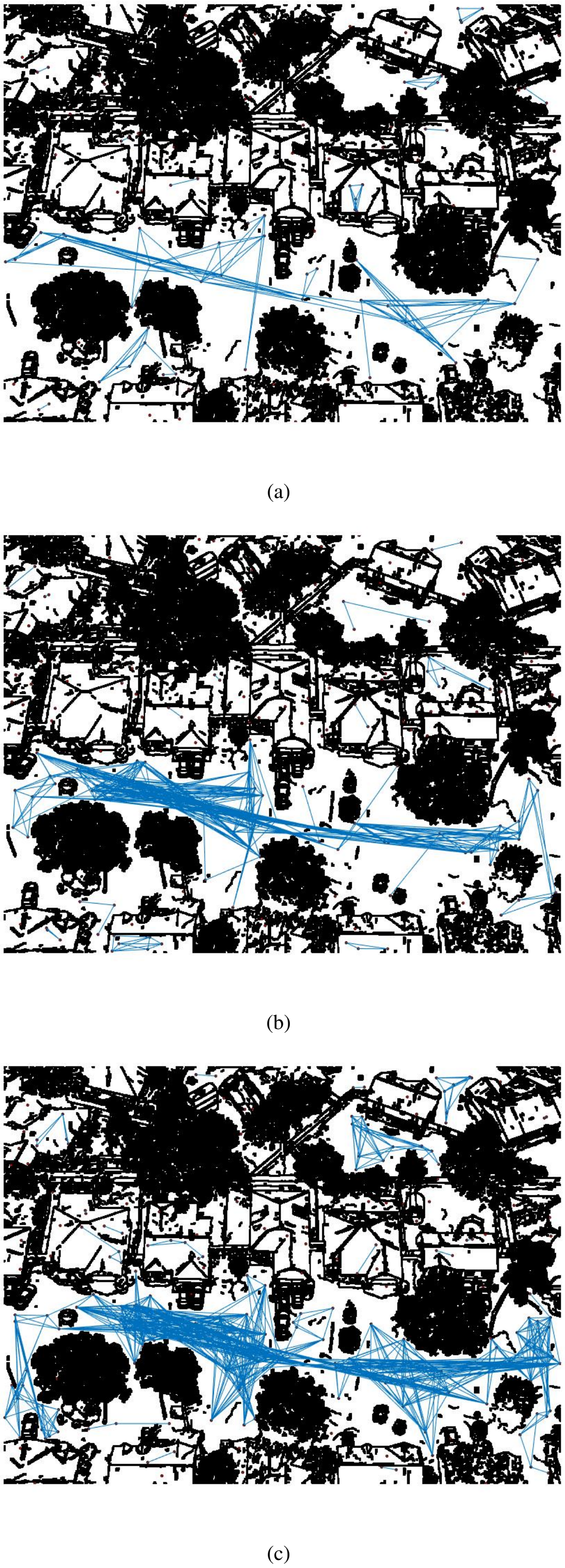

Fig. 11. (a) Roadmap with 100 nodes (b) Roadmap with 150 nodes (c) Roadmap with 200 nodes

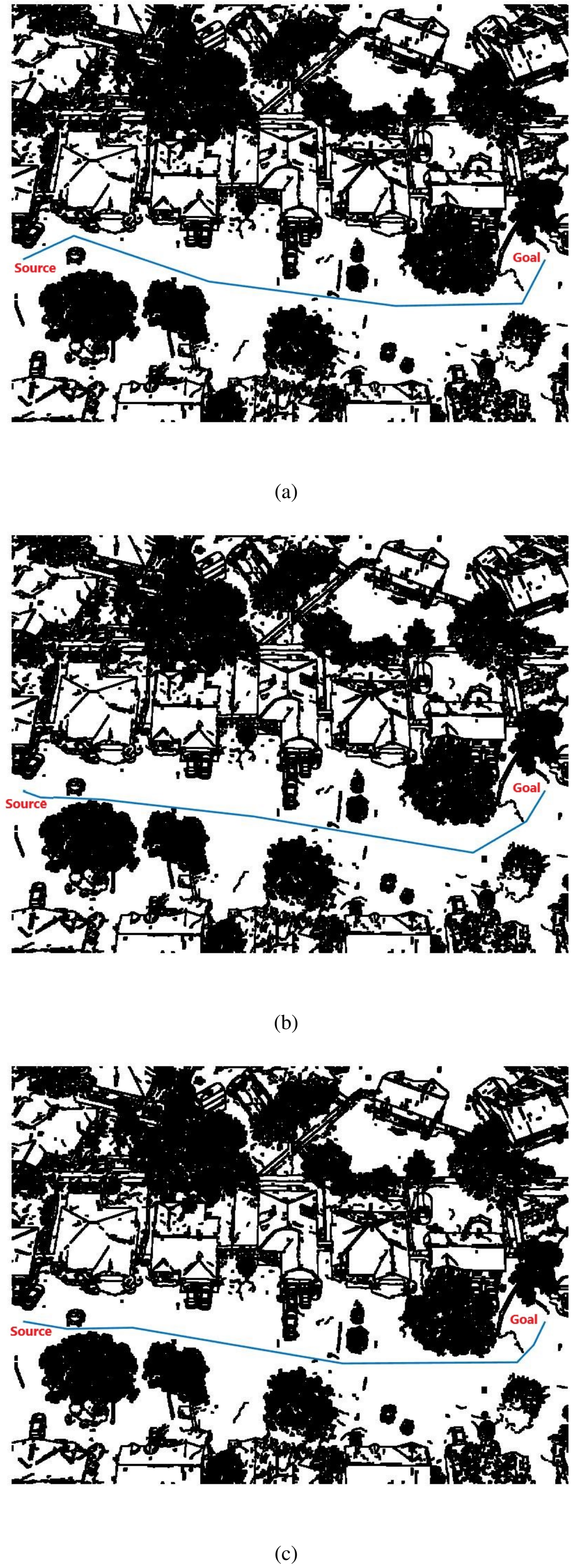

Fig. 12. (a) PRM path with 100 nodes (b) PRM path with 150 nodes (c) PRM path with 200 nodes

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