Group project Report

AI Path Planning
- Introduce a new algorithm based on VNS for the Artificial Potential Field Method to avoid local minima

Tutor: Zibo Wang

Group members: Yixi Rao, Chun Wu, Yifan Li

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Question 1

Our research introduces a new algorithm based on VNS for the artificial potential field method to avoid local minima.

Khatib first introduced the Artificial Potential Field (APF) [9] method into obstacle avoidance path planning for robots. The basic idea is to treat robot movement in the planned space as a movement in the virtual force field. Obstacles have negative potential energy, which causes a repulsive force on the robot, and target points have positive energy, which produces an attraction to it (Figure 1.1). The robot moves towards the target by adding the attractive force and repulsive force together which generates the resultant force. The artificial potential field method is of low computational complexity and can obtain a smooth, trustworthy, and complete path.

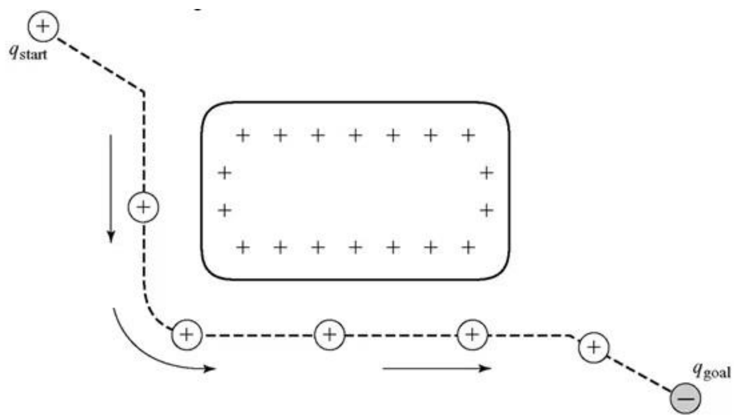


Figure 1.1

However, the traditional APF method has some problems:

1. Goal non-reachable with obstacles near the target (Figure 1.2). “It means that the robot would fall into the local minimum point of the potential field in advance before reaching the target point and is unable to reach the target.” [10]

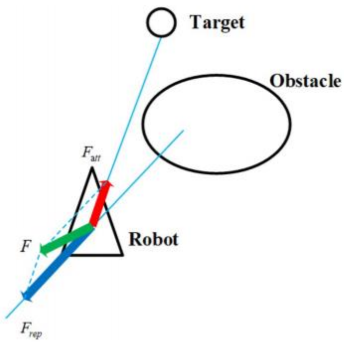


Fig. 5 The situation that obstacles are relatively close to target

Figure 1.2

2. Goal non-reachable with resultant force equals 0 (Figure 1.3). “Where the combined field is zero, Fatt and Frep cancel out each other, which makes it difficult for APFM to judge trajectory, or even causes the local optimal solution problems” [11]

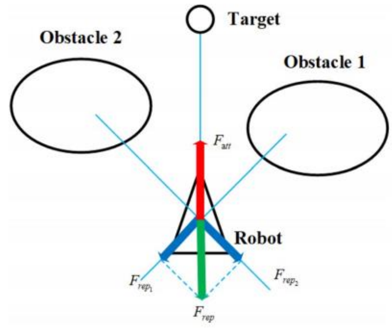


Fig. 4 The situation that combined field is zero

Figure 1.3

Therefore, this research paper demonstrates a solution to solve these local minima problems of the traditional Artificial Potential Field (APF) method to obtain a full, smooth and optimal path towards the target.

Question 2

When it comes to path planning problems, there are two categories. One is path planning with differential constraints, and the other one is path planning without differential constraints. By performing several pieces of research, path planning problems with differential constraints is essential because it is the base of path planning problems with differential constraints. When it comes to problems with constraints, more complicated algorithms should be figured out. Therefore, fundamental path planning algorithms should be comprehended to solve more complex planning problems.

Specifically, the artificial potential field method is a path planning method without differential constraints which means it is worth researching.

In addition to this, when non-experts are encountered with path planning problems, the most likely intuition is using geometric algorithms to solve such problems as dividing spaces or using graphs. However, the artificial potential field method is an innovative method that extracts a physical algorithm from the traditional geometric algorithm and places the path planning problem into a virtual force space.

Nevertheless, the artificial potential field method produces a more intelligent and exciting way of simulation. The positive energy of obstacles generates repulsion on the robot, and the negative target generates attraction. This simplifies the complicated path planning algorithm into a method with low computational complexity and good obstacles avoidance performance.

However, the path generated by the artificial potential field method have good performance on path planning problems but is not necessarily the optimal obstacle avoidance path. Therefore, the future research direction should focus on implementing the function of finding the optimal path [12].

By doing plenty of research, we find a method called Variable neighbourhood search (VNS). "VNS algorithms work by repeatedly chaining (i) a descent phase through a systematic change of neighborhood providing local improvements to an existing solution; and (ii) a perturbation phase aiming at escaping the valley of the local optimum reached during the descent phase" (Bit-Monnot, 2018, p.2) [13].

Our motivation for this specific method is that one of the critical benefits of VNS is its very generic and adaptable definition [13]. Moreover, each neighbourhood proposes a local plan adaptation that improves a particular solution [13]. Our motivation also comes from that no considerable effort has been made to apply the VNS technique to APF.

Question 3

Overall summary

To solve the problem of GNRON in the traditional APF approach, early research mainly improved the traditional method from three aspects, which is potential field function model modification, adding an appropriate escape algorithm at local minima and combining the artificial potential field with other methods.

In the aspect of APF function model modification, the local minima can be eliminated or reduced by constructing a new and reasonable potential field function or modify the repulsive potential field function. Based on the Laplace equation, a potential field function without minimum points is introduced by Sato [1]. Therefore, path planning is carried out without falling into local minimum, but it does not consider whether planned path is optimal or not. [2] uses the Gaussian function to build the potential function which can reduce the probability of local minima appeared during planning. In terms of modifying the repulsive potential field function, Ge and Cui introduced the relative distance approach which is a distance between goal and the robot, and this is added into the repulsive potential function [3], the new repulsive potential function can guarantee that the goal position potential has the global minimum value.

The effect of Revising the potential field function is there is only one global minimum value and local minima are eliminated, however, if the robot is already stuck at the local minimum and there is no external force or some other algorithms, the robot will not be able to get out of the area. In this case, many studies have focus on developing an escape algorithm, the main idea is utilizing some search strategies to escape from the local minima or detecting the local minima in advance to achieve local minima avoidance, after getting away from the local minimum successfully, the robot will continually follow the negative gradient of the potential field function unless it falls into the local minima again or it gets to the goal. Janabi and Vinke [4] introduce integration of the APF approach with the simulated annealing (SA), the simulated annealing technique is applied when trapped in local minima. Using the potential function to be the cost function, at each step, SA approach chooses a new position P' from a set of neighbours of the current position P, P' is accepted unconditionally if U(P ') <= U(P) or else with probability of $e^{-(U(P') - U(P))/T}$ where T is the temperature. The limitation of APF with SA is that the simulated annealing largely depends on the setting of parameters such as the initial temperature and the cooling rate. Sometimes the inability to find a suitable parameter set causes the robot to be unable to get rid of the local minimum. Furthermore, most approaches are based on the local search approach, for example, literature [5] is based on the basic idea of genetic algorithm, which sorts the attractive potential coefficient, repulsive potential coefficient, the influence distance of the obstacle and the step size of the robot into an array in order as a chromosome, and then search for the path. The quantum particle swarm algorithm [6] not only can escape from the local minima but also can generate dynamic path for the dynamic environment.

An Algorithm based on the Deterministic Annealing Approach [7]
– Yixi Rao summarized

The major problem of APF is the goal not reachable problem due to the local minimum, therefore, there are serval approaches are used to solve it and they were classified in three categories:

- Local minima removal (LMR) [7]
- Local minima Escape (LME) [7]
- Local minima avoidance (LMA) [7]

The LMR method can fundamentally solve the problem, but it is very depending on the certain types of obstacles. LME approach can help the robot escape from the local minima, but the planned path is very inefficient and not smooth, besides, the LME relies heavily on parameter sets. In this context, a new method based on deterministic annealing is introduced in this paper in 2013, which can be classified as LMA (Doria, 2013, p.2) [7].

The deterministic annealing approach is inspired by the simulated annealing, the improvement is that DA avoids the random movement, which is a limitation associated with the SA. The potential function of the proposed new approach is inserted with a new parameter temperature, so the traditional potential functions are modified as follows:

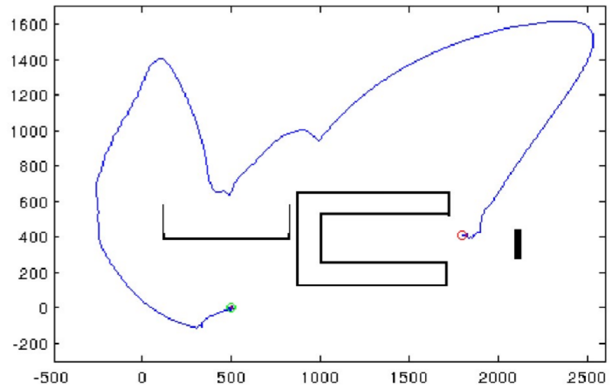
$U_{att} = \frac{1}{2} \cdot k_{att} \cdot \frac{d(cur,goal)^2}{T}$

$U_{rep} = \frac{1}{2} \cdot k_{rep} \cdot \left(\frac{T}{R} - \frac{1}{d(cur,obs)}\right)^2$, if $\frac{R}{T} \leq d(cur, obs)$

Where T denotes temperature.

Consequently, the coverage of the repulsive potential of the obstacles will increase and the value of the repulsive potential will also increase with high value temperature, meanwhile, the attractive potential will decrease. In the LME-DA, when the robot is captured at a local minimum, the temperature will start to rise until the robot escape from the local minimum. The LME-DA is an intermediate step of LMA-DA, in the LMA-DA, the temperature is set at a remarkably high temperature at the beginning, and the temperature is slowly and progressively cooled down over time [7]. As a result, the behavior of the robot will be like the robot will gradually move far away from all the obstacles, and then slowly move closer to the goal as time goes by. The advantage of this approach is that it can detect the global minimum (goal) early and easily, in addition, the LMA-DA can be applied in an unknown environment minor revision, which is adding the LME-DA approach when the robot falls into local minima [7].

The simulation result of this paper is the LME-DA approach can produce a smoother path than the LME-SA, however, both paths are inefficient with some redundant waypoints, this is due to the nature of the simulated annealing method, another limitation of the LME-DA is that It is very dependent on the set of parameters used, and it is impossible to find a parameter sets that can help robot escape from the local minima. For the LMA-DA approach, it can achieve the avoidance of local minima, even in some extraordinarily complex cases, such as U-shaded obstacles. The limitation of the LMA-DA is still the problem of inefficient path, this is happened when the initial temperature is extremely high that expels the robot move far away from the goal like in the figure 3.1. So, we should consider the aspect of how to find an optimal or suboptimal path on our development of our new approach.



(d) LMA-DA

Figure 3.1

An Algorithm combining Artificial Potential Field Method with Reinforcement Learning [8]
– Yifan Li summarized

The relevant state of the art paper is: “An obstacles avoidance method for serial manipulator based on reinforcement learning and Artificial Potential Field” [8]. This paper demonstrates a novel method of combining the artificial potential field method with reinforcement learning (RL-APFM) to resolve path planning problems [8].

This RL-APFM is an offline algorithm that the agent should know the potential field environment, and it gets two more factors than traditional APFM: Distance Reinforcement Factors (DRF) and Force Reinforcement Factors (FRF) [8].

A value function takes the agent’s current state during a reinforcement learning process and outputs a behavior. Then the interactive environment reacts to this behavior and updates the state of the agent. The agent then creates a new attribute value from the value function, and the iteration occurs. Due to the characteristic and benefits of reinforcement learning, RL-APFM can obtain optimal path planning.

The attractive and repulsive function remains the same as traditional APFM. This paper updates the traditional RL reward and Q-function notations by splitting them into DRF and FRF, respectively and generating new resultant force to perform path planning. The distance between the robot and the obstacles determines the DRF, and the collision force between them determines the FRF [8].

In order to implement RL-APFM, traditional APFM should firstly find the path given the obstacles located. Then, DRF is activated when the robot enters the influence region of the obstacles and pushes the robot away from them. Moreover, FRF is activated when the robot collides with obstacles, letting the robot escape from them as soon as possible. Ultimately, this algorithm finds the optimal RL rewards in iterations to avoid collision and reach the target. The figure 3.2 below shows the procedure of operating RL-APFM.

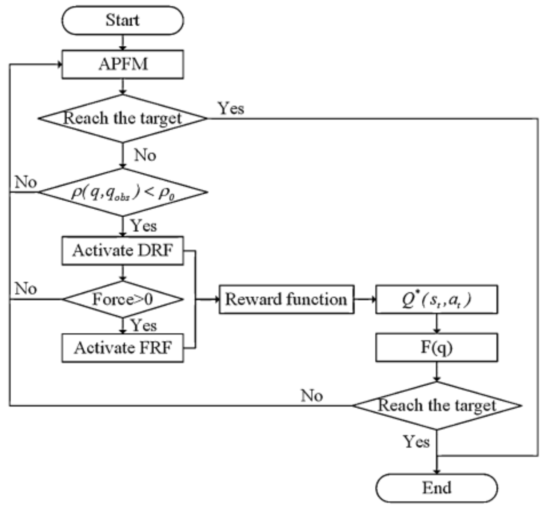


Fig. 6 Flow diagram of RL-APFM

Figure 3.2

To verify this RL-APFM algorithm, the researchers conduct a simulation with the statistic obstacles environment and dynamic obstacles environment with and without collision. Comparing RL-APFM with traditional APFM in simulation, RL-APFM gets better performance to reach target closing to obstacles while traditional APFM is likely to fall into local minima. Furthermore, with dynamic obstacles, traditional APFM cannot avoid them, but RL-APFM succeeds with non-collision. If taking the time and space complexity into account, RL-APFM can successfully avoid obstacles more efficiently and with faster iterations given the same simulation condition.

In addition to this, researchers also verify the RL-APFM algorithm to operate physical experiments with static and dynamic obstacles environment. The result shows that RL-APFM can avoid obstacles with and without collision in a static and dynamic environment. Also, it shows better performance when the target is closed to the obstacles.

Therefore, this paper concludes that RL-APFM performs well with dynamic obstacles, eliminates local minima, and arrives at the target when it is closed to the obstacles, which are the fundamental problems of traditional APFM. The RL-APFM algorithm can be successfully implemented into a real robot to perform obstacles avoidance.

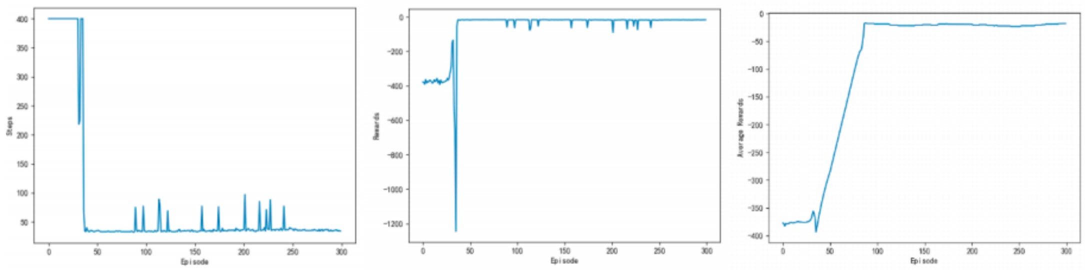
An Autonomous Path Planning Model for Unmanned Ships Based on Deep Reinforcement Learning [19]
– Chun Wu summarized

The relevant state of the art paper is: “Improved Model of Autonomous Path Planning” [19]. This paper introduces using Deep reinforcement learning (DRL) approaches, specifically of Deep Deterministic Policy Gradient (DDPG) into path planning problems. Furthermore, this paper combines DDPG with traditional Artificial potential field (APF) methods (DDPG-APF) to solve autonomous path planning problems on ship models.

Though path planning approach based on DDPG algorithm could has better planning effect, the generated path is redundant and not sufficiently flat [19]. Therefore, this paper investigates on the training process, and it is found that DDPG has a relatively low-efficiency training cycle due to low rate of convergence speed. The above phenomenon is because the DDPG has no prior knowledge of the environment and the initial stage of learning can only randomly select actions [19]. Thus, Using APF method, as pre-defining the target point and obstacles by applying gravitational field and repulsive field in the environment, could construct the necessary position information while excluding the invalid unsearched iterative search spaces.

The paper constructed the DDPG-APF algorithm. The algorithm is within similar framework of traditional APF method. Firstly, it constructed the potential field and the obstacles, and set the target point as the center of the potential field. Secondly, the algorithm defines the potential energy value $U(S_i)$, and the cumulative report $V(S_i)$. Then replacing the selecting action process of APF with Updating Q value according to the state value function, and subsequently update the information into the online Critic network of DDPG algorithm [19].

To verify the training process of the constructed algorithm is of good efficiency, the paper shows relative data of the training process. In Figure 25, It shows the training process of APF-DDPG. From Figure 25a, it can be seen that the number of training steps in each round begins to decline and converge in the 43th round. Thus, this paper showing that the APF-DDPG training process is relatively low cost and with optimized convergence speed.



(**a**) Number of steps per turn. (**b**) Cumulative return value per turn. (**c**) Average return per rounds.

Figure 25. Artificial potential field-DDPG (APF-DDPG) training process.

Moreover, by comparing the case generated by DDPG and DDPG-APF in Figure18 and Figure 26, it shows Figure 18 has more redundant and longer path while the path generated by DDPG-APF in Figure 26 is relatively smoother and shorter path. By comparing the two results, it is shown that the DDPF-APF has better decision-making level and faster convergence speed [19].

Figure 26. Experimental results based on APF-DDPG (a).

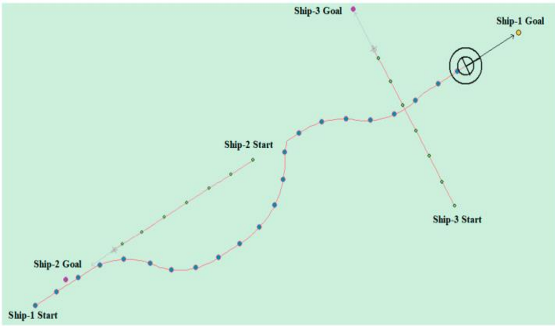


Figure 18. Verification result of ship trajectories in multi-ship encounter case 1.

The paper also extracted experiment data made from the core aspects pf neural network training, comparing the DDPG-APF with others. As is shown in Table 12, the DDPG-APF has higher convergence speed and stability [19].

Table 12. Comparison of experimental data.

Comparative Experiment	Total Iteration Time (s)	Optimal Decision Time(s)	Convergence Steps	Number of Collisions
DQN	452.512	410.856	235	139
AC	361.219	332.463	136	84
DDPG	338.713	281.651	122	72
Q-learning	486.321	437.245	260	175
APF-DDPG	294.960	236.152	68	63

Therefore, this paper concludes the derived planning method based on the DDPG algorithm could generate efficient and actual-usable path with relatively high accuracy, while the traditional APF method could not store and recycle the past experience resulting in the low accuracy of the algorithm. The reinforcement learning approaches combines with APF method successfully create a new autonomous path planning method.

Question 4

Initial approach and intuitive solution

This research demonstrates a solution of dealing with local minima problems of traditional artificial potential field method. Firstly, we determine to implement original APF in the code because we want to examine the existing problems of traditional APF and verify our new ideas more intuitively.

However, before implementing APF, we should acknowledge that most of the obstacles hold an irregular shape for path planning problems in real life. It leads to problems that it is challenging to write code for complex obstacles. Therefore, we made the thing easier by using point obstacles to represent real obstacles with their respective influence region. Point obstacles have a high representation power because obstacles of different shapes, for example, polygons, can be approximately represented as a combination of point obstacles. Figure 4.1 shows an example of point obstacles representing trapezoid, triangle and rhomboid, which reveals point obstacles are worthy of being implemented to represent most kinds of obstacles.

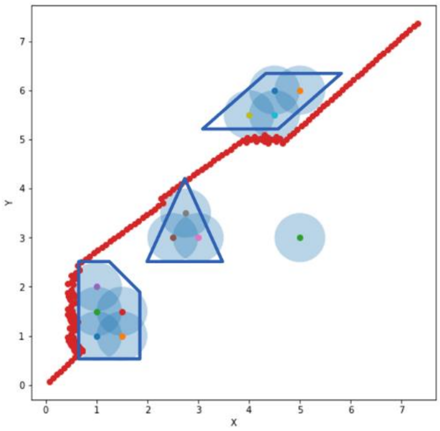


Figure 4.1

To implement the original APF, we first determine the definition of it. Our APF an offline algorithm that the potential field environment is established, and the robot can acquire knowledge of the potential environment.

After ensuring this definition, we create a class APF (), containing all valuable variables and functions for path planning. Because our APF is set on a discrete Cartesian coordinate system, the robot can only move in a fixed step size, and each waypoint of the robot will be appended to the planning path. We aggregate these variables and functions and execute path planning successfully. Figure 4.2 explicates the result of our original APF with a starting point (0,0) and a target point (5,5).

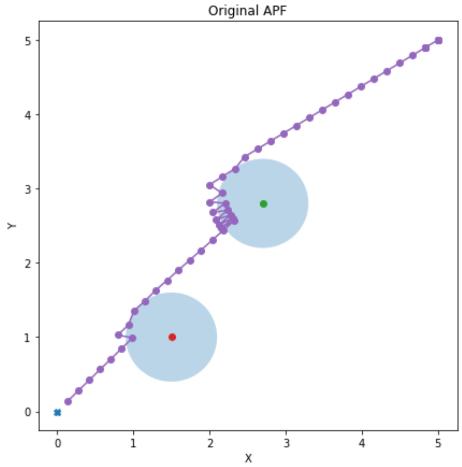


Figure 4.2

To evaluate the functionality of this traditional APF, we try different obstacles lists and find some instances of goal non-reachable cases. Figure 4.3 shows that the robot fails when the resultant force on the robot equals zero. Figure 4.4 shows when the obstacles are gathered but with gaps inside, the robot will fall into local minima.

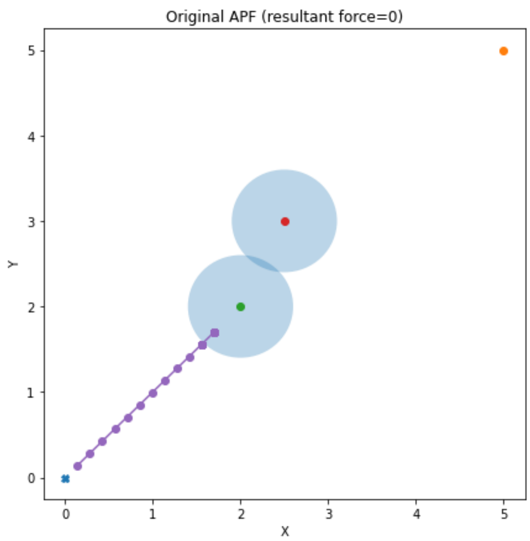


Figure 4.3

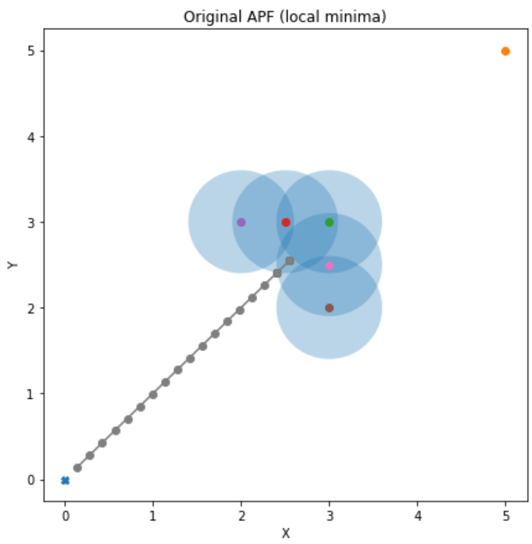
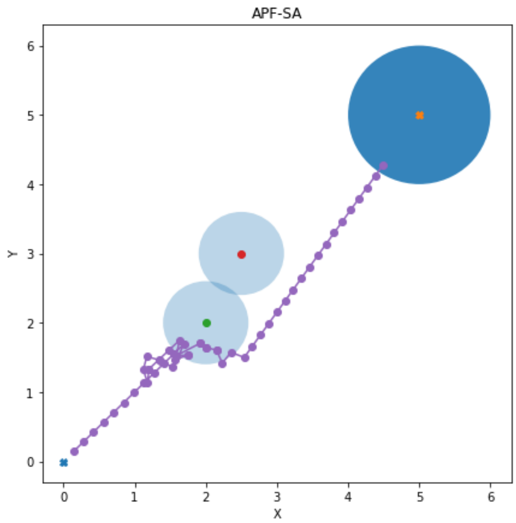


Figure 4.4

To address the embedded problems of the traditional APF method, researchers mainly conclude with two approaches. The first is modifying the potential field function model. The second is adding appropriate escape strategies. Combining Simulated Annealing with traditional APF is an example of the second approach. Because SA is an easy method to comprehend and achieve, we decide to implement this APF-SA to evaluate how it works and give us inspiration for our method. Both Figure 4.5 and Figure 4.6 shows the result of APF-SA. Figure 4.5 is configured with the same environment as Figure 4.3, where the resultant force will become zero. Figure 4.6 takes the same environment as Figure 4.4, where the robot may fall into local minima. Hybridizing SA and traditional APF method get an acceptable outcome. Although the path it obtained is not optimal because there are noticeable vibrations at the edge of the obstacle, this APF-SA can be a good comparison tool when experimenting with our new method.



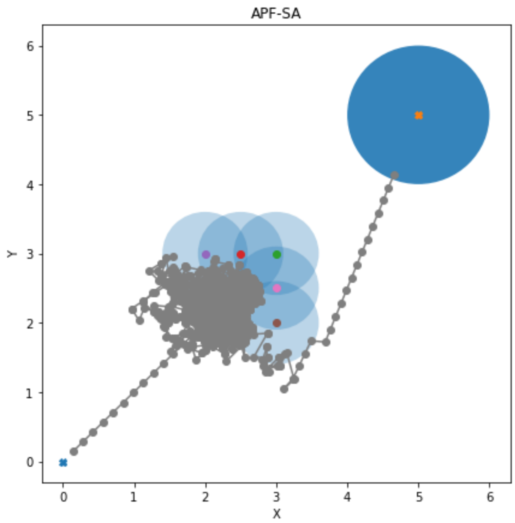
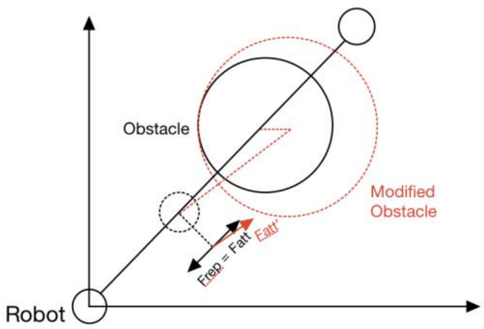


Figure 4.5 Figure 4.6

To develop a new method of solving local minima of the traditional APF method, it is worth having some brainstorm of potential solutions. The condition that resultant force comes zero only occurs when the center of the obstacle is collinear with the robot. Therefore, our intuition is changing the position of the obstacle little to avoid collinearity. As the background of our method is an off-line algorithm, we can replace the position of obstacles by a little degree, as Figure 4.7 shows. After implementing this idea into real code, Figure 4.8 shows that the robot can successfully reach the target when the environment is identical to Figure 4.3.



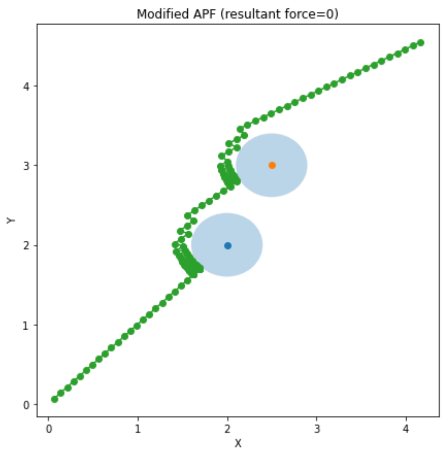


Figure 4.7 Figure 4.8

In addition to this, the robot will fall into local minima with connected obstacles having gaps inside. The reason for this situation is that the shape of the connected obstacles is concave that the robot will produce vibrations along the edge of obstacles and fall into local minima. The intuition solution of this problem is filling the obstacles to make a complete and convex polygon. Figure 4.9, 4.10 and 4.11 display the comparison results of swelling obstacles. The result demonstrates that the filling method accomplishes the goal since the robot reaches the target.

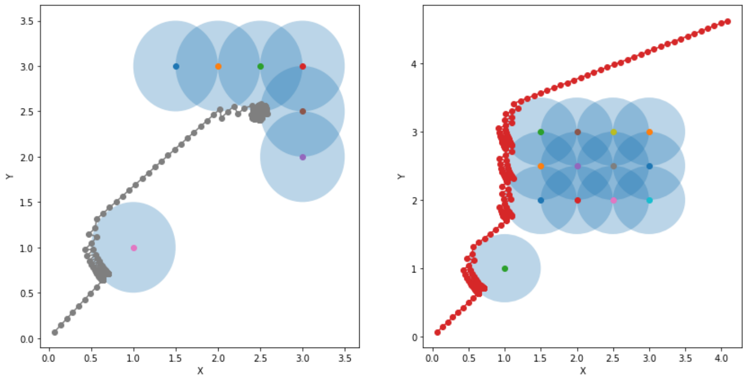


Figure 4.9

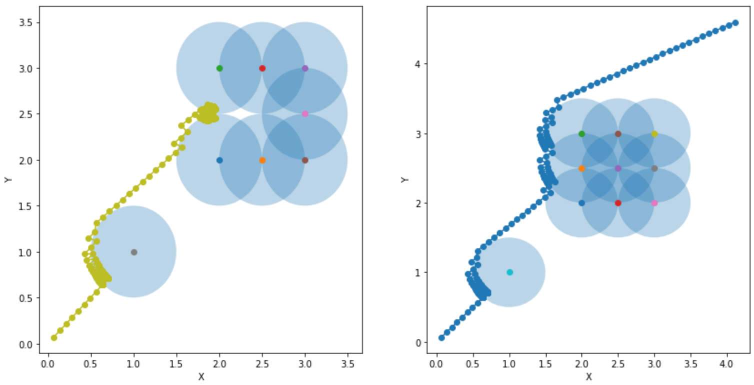


Figure 4.10

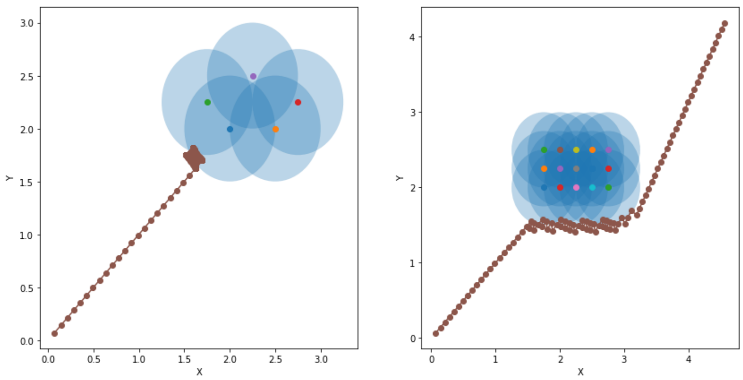


Figure 4.11

Although changing the center of obstacles (solving resultant force being zero) and filling the irregular obstacles (solving the local minima) can succeed the two problems of the traditional APF, both approaches lead to the increase of the obstacle influence region. Especially, the consequence of filling the obstacles is not acceptable. Because of this, the path we obtain is not optimal at all. Therefore, a more robust and complete algorithm should be introduced to fully tackle the problems of the traditional Artificial Potential Field method.

New approach

To deal with the inefficient path problem, we design a new approach based on the variable neighbourhood search. We analyze state of the art and conclude that to generate an optimal or suboptimal path, the necessary condition is the implementation of the LMA and avoid using LME. This is due to the redundant waypoints produced in the escape phase of LME. On the other hand, we found that if there are no obstacles, the robot will find an optimal path because the artificial potential field method using the gradient descent method which will find the direction of the fastest gradient descent [15], consequently, we decide to manipulate the paths that have been generated to solve the problem and this is the basic idea of the local search approach. Among many local search algorithms, one of the powerful techniques for avoiding the local minima is the variable neighbourhood search approach applied to the graph colouring problem, minimum spanning tree problem, Knapsack problem, and TSP problem [16], etc. However, the application of variable neighbourhood search technique to APF has not been studied enough. This is an applicable method for solving our problems for several reasons:

- We want the planned path that avoids the local minima and is more efficient simultaneously. Moreover, one of the critical benefits of VNS is that each neighbourhood improves a particular aspect of the solution. Therefore, two or more neighbourhoods can be designed to achieve optimality and achieve LMA.
- We need some random factors to deal with the complex environment because the robot does not know how many local minima will be encountered.

Using a proper and robust objective function, we can let the robot find a globally optimal path concerning all possible neighbourhood structures. This path can avoid as many obstacles as possible rather than avoid the obstacles that cause the local minima problem.

To apply this new approach based on the variable neighbourhood approach to the local minima avoidance, we should deal with two types of issues. First are problem-specific issues: the definition of VNS, solution, initial solution, shuffling function, local search heuristic, and the neighbourhood in APF environment. Second, the path evaluation issues include the factors affecting the quality of the path and the construction of the objective function. Two types of issues will be introduced in the next section.

1 VNS

"Variable neighbourhood search (VNS) is a metaheuristic or a framework for building heuristics" (Pierre, 2010, p.368) [16]. "VNS algorithms work by repeatedly chaining (i) a descent phase through a systematic change of neighborhood providing local improvements to an existing solution; and (ii) a perturbation phase aiming at escaping the valley of the local optimum reached during the descent phase" (Bit-Monnot, 2018, p.2) [13].

We choose the basic variable neighbourhood search (BVNS) in the artificial potential field problem because the BVNS combines deterministic and stochastic changes of the neighbourhood [16]. We require the stochastic neighbour in the neighbourhood to help the robot to avoid the local minima. The BVNS algorithm is described in figure 1. On the other hand, some other versions are inapplicable to this situation. For example, no descent is made in the Reduced VNS (RVNS) [16], and the General VNS (GVNS) using the Variable Neighbourhood Descent (VND) local search scheme that is more suitable for the change of neighbourhoods is performed in a deterministic way [16].

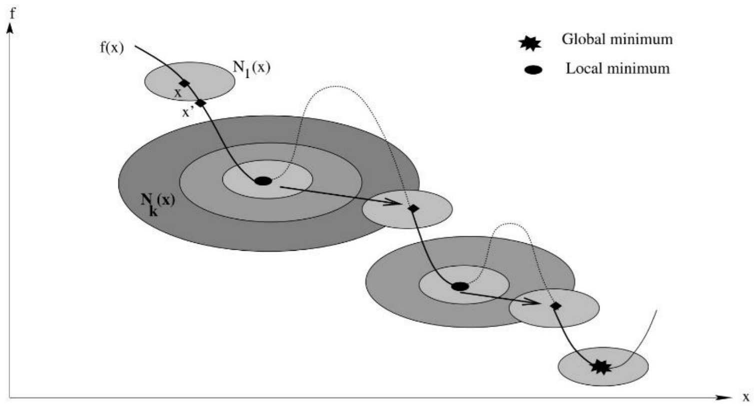


Fig. 1 Basic VNS

1.1 local search heuristic

In the VNS, a local search is embedded in (figure4.12), the local search heuristic is finding the best local neighbour within a specific given neighbourhood. The local search heuristic used in VNS is the Best improvement heuristic (figure 4.13), finding the steepest descent direction by a given solution. We choose the best improvement instead of the First improvement heuristic because [16] previous experience suggests that if the initial solution is constructed reasonably, then the best improvement rule should be applied. For our situation, the initial solution is generated by using the current path, so using the best improvement rule would be better.

Function VNS($x, k_{\max}, t_{\max}$);
repeat
  $k \leftarrow 1$;
  repeat
    $x' \leftarrow$ Shake(x, k) /* Shaking */;
    $x'' \leftarrow$ FirstImprovement(x') /* Local search */;
    NeighbourhoodChange(x, x'', k) /* Change neighbourhood */;
  until $k = k_{\max}$;
  $t \leftarrow$ CpuTime()
until $t > t_{\max}$;

Algorithm 7: Steps of the basic VNS

Figure 4.12

Function `BestImprovement`(x);
repeat
  $x' \leftarrow x$;
  $x \leftarrow \arg\min_{y \in N(x)} f(y)$
until $(f(x) \geq f(x'))$;

Algorithm 2: Best improvement (steepest descent) heuristic

Figure 4.13

1.2 Shuffling function

The shaking function is essential in developing an effective VNS because it controls the trade-off between diversity and convergence. We do not want our VNS to coverage early since the robot might be caught by the local minima again. Besides, if the VNS excessively focuses on diversity, then the path might be less efficient. Therefore, we choose to use only a fraction of the solution to shake.

2 Definitions

This section will introduce some basic definitions of the proposed approach. APF configuration is the same as the original APF configuration mentioned above.

2.1 Definition 1 (Solution) given a path Π, and a maximum sub-goal number K, the solution is a list of sub-goals and each sub-goal SGi ∈ {1…k} ∈ Π.

Our new approach is a list with a fixed number of sub-goals, which will help the robot avoid the local minima. In our new approach, whenever a local minimum catches the robot, the sub-goals are extracted from the current path. The robot's current position will backtrack to a specific point of the current path; the robot must reach all the sub-goals before moving to the real goal.

Early research uses the sub-goals to solve the goal non-reachable problem separately. For instance, Bell and Weir (2004) propose a new sub-goal algorithm that starts from an initial location. Then the robot chooses a sub-goal from the range of a half-circle arc with a fixed radius D. when the robot reaches the sub-goal or cannot reach the goal for a long time, it will a find new sub-goal [17].

2.2 Definition 2 (Neighbourhood): A neighbourhood N defines a set of neighbour solutions for each valid solution. N(SGi) ⊆ Πall, where Πall is the set of all valid solution [13].

In our approach, we define some classes of neighbourhoods related to the shifting of the position of the sub-goals, and each neighbourhood has its policy of displacement pattern. Each neighbourhood contains eight neighbours. There are serval neighbourhoods used, and they were classified into three categories.

- **Coordinate translation neighbourhood**:

- **Move up (down, left, right) neighbourhood**: each of the eight neighbours in this neighbourhood has varied sizes upward (downward, leftward, rightward) offset on the sub-goals, note that each sub-goal in one neighbour has the same amount of offset but different with other neighbours.
- **UDLR neighbourhood**: this neighbourhood randomly selects a direction (Up, Down, Left, right), then reuse the above neighbourhood.

- **Random neighbourhood**:
  - **Random eight directions neighbourhood**: each sub-goal in the neighbour solution randomly selects a new sub-goal from eight directions of the range of a circle with a fixed radius D, where D can be the step size or half of the step size.
  - **Random all direction neighbourhood**: each sub-goal in the neighbour solution randomly selects a new sub-goal from the range of a circle with a fixed radius D, where D can be the step size or half of the step size.

- **Local path optimization neighbourhood**:
  - **Obstacles-free neighbourhood**: The new sub-goal will avoid the obstacles as much as possible, preferably if it is entirely outside the obstacles. See figure 4.14 & 4.15.
  - **Highest-possibility neighbourhood**: The new sub-goal selected is the farthest from the nearest obstacle.

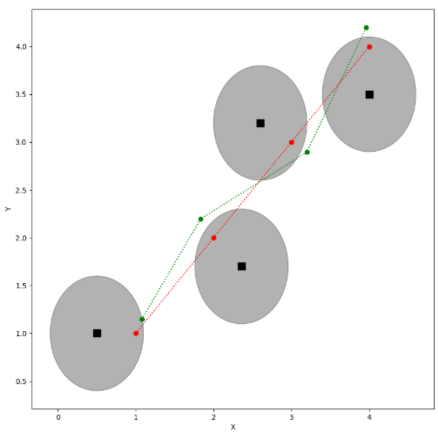


Figure 4.14

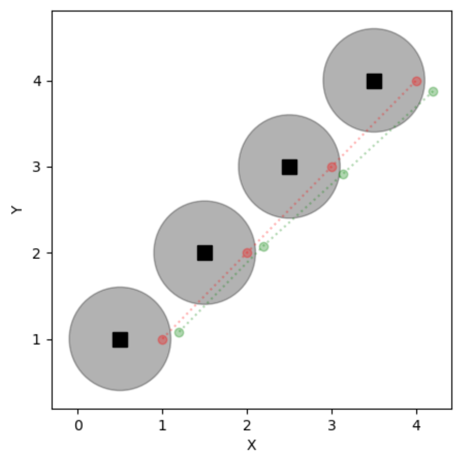


Figure 4.15

3 Evaluation

Now that we have many feasible solutions in the neighbourhood, we need a proper and robust objective function to filter out the best solution. We want the best solution to have two essential properties. i) It can achieve the local minima avoidance ii) The shorter, the better, if property one is satisfied.

For the first property, we observed some experiments and draw conclusions from previous studies, paths that can avoid the local minima rarely pass through the coverage of the obstacle, and even if it goes through some obstacles, it does not get too close to the center of the obstacle. To measure the influence of obstacles on the path, we focus on two aspects: measure the influence on the sub-goals and influence on the edges (an edge between each of the two sub-goals). We decide to use the potential function to measure the influence because the repulsive potential function value will increase when the sub-goal or edge is very close to the center of the obstacle. We want this measurement's value to be as large as possible.

$$U_{all}(N_i) = \sum_{i=0}^{n} U_{att}(SG_i) + (-\, U_{rel}(SG_i))$$

$$U_{edge}(N_i) = \begin{cases} \sum_{i=1}^{n} \frac{1}{2} \cdot \beta \cdot \left(\frac{1}{h_{(i,i-1)}} - \frac{1}{Q_r}\right)^2, & h_{(i,i-1)} \leq Q_r \\ 0, & h_{(i,i-1)} > Q_r \end{cases}$$

where h is the shortest distance from edge to obstacle center.

For the second property, the measurement can be made by evaluating the path length. Hence, the total path length summarises the distance from the current position to the first sub-goal, the distance between all the sub-goals, and the distance from the last sub-goal to the goal.

$$D_{path}(N_i) = d(cur, SG_0) + \sum_{i=1}^{n} \big(d(SG_i, SG_{i-1})\big) + d(SG_n, Goal)$$

The objective function is a linear combination of all three evaluations with different coefficients (or weight). We want the value to be as considerable as possible, so we make the D_{path} and U_{edge} negative. The higher the value, the more likely it will achieve the two properties as mentioned above.

$$f(N_i) = a \cdot U_{all}(N_i) - b \cdot D_{path}(N_i) - c \cdot U_{edge}(N_i)$$

Question 5

	Literature analysis	New Methods and Ideas	Code	improvement	contribution
Yixi Rao	Read some peer APF reviewed papers like [10], [17]. And In our group, I am responsible for analyzing paper related to LME escape algorithm. E.g. [4], [5], [7], [13]	Propose the new approach based on VNS and evaluation part. suggest that we can conduct a comparative analysis between APF_SA and APF_VNS	Write the basic framework of the new approach and the APF, and Responsible for the VNS algorithm. Write the *coordinate translation neighbourhoods* and *random neighbourhoods.*	Propose the best Improvement local search heuristic would do better than the first improvement heuristic. And change the GVNS to BVNS.	33%
Yifan Li	Read APF reviewed papers such as [10]. Perform in-depth study in literature [4] which generates APF-RL. Review paper [18] of APF + Genetic Algorithm.	Come up with all the intuitive solutions. Verify the representation power of point obstacles. propose the combination of APF_VNS and RL. propose we can have some derived research of testing the different combination of neighbourhoods...	Write the obstacle filling intuitive solution and the obstacle center moving intuitive solution. Write some local path optimization neighbourhood e.g., *obstacle free* and *highest-possibility*,	Discover the potential problem of ZeroDivisionError and some edge problems, and write a new version of the *U_edge* function and also improve the objective function	33%
Chun Wu	Read APF reviewed papers [10], [21]. And to construct goal recognition part, paper [20], and paper [19], [22] regarding using Reinforcement Learning to improve APF algorithm.	Come up with and design the environment setting of the map. Contributed to the evaluation part. Proposed using RL DDPG method for improvement of VNS-APF	Responsible for the new approach visualization and the potential function visualization and adding RL approaches, write the framework of DDPG Write the *neighbourhood_optimize_edge* Neighbourhood.	Identify the problem of dense sub-goals problem, write the new version (*dividePath2*). Make an animation of the new approach.	33%

The functions and neighbourhoods mentioned in the tabular can be checked on https://github.com/Yixi-Rao/APF (Yixi branch, LMA_VNS_APF.py)

Why did you distribute the work in that way?

The basic idea of adding VNS approaches into artificial potential field algorithm to solve Goal non-reachable problem is based on Yixi Rao's proposal, thus we decided the task of completing the basic framework of VNS is in the charge of Yixi Rao. Before actually implementing VNS with APF, Yifan Li got some intuition of solving the APF problems and implemented these solutions in code. Although it got some improvement, the result was less than satisfactory. Therefore, through first meeting, we discussed furtherly about VNS, especially the composition of different sorts of "neighbours" usage, and decided the "*neighbourhood_optimize_edge*" should be in the charge of Chun Wu, and "*neighbourhood_obstacle_free*" should be in the charge of Yifan Li. After completing the basic framework of our VNS-APF method, through second meeting, we analyzed the current progress of the project, and the current problems of our method. Therefore, in this period, Yixi was in charge of testing the remaining problems, Yifan Li was in charge of solving some edge problems and applying the improvement RL-APFM method and Chun Wu was in charge of building DDPG algorithm framework to further complete APF improvement method.

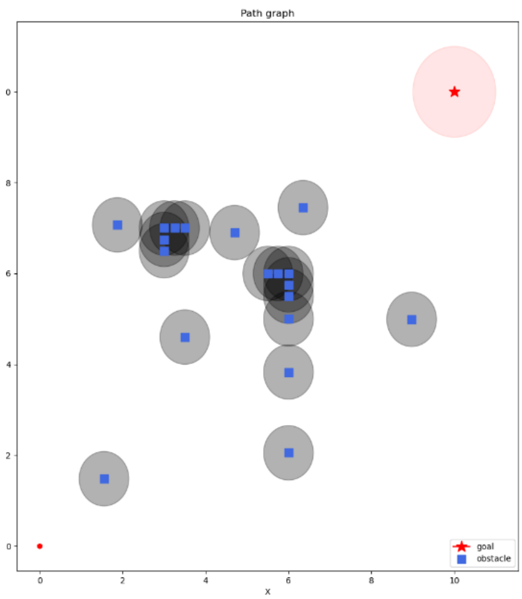
Question 6

Experiment I: Our research question

To present the ability of local minima avoidance and to verify the efficiency and the effectiveness of the proposed approach, the proposed method is compared with the following methods through simulation and experiment:

- **The original APF:** the original APF method with no extension to deal with the local minima, the aim of using this is to demonstrate that such a local minimum exists in each environment.
- **APF with SA:** an LME method based on the simulated annealing approach, the purpose of using this contrast is to demonstrate the effectiveness of our new approach.

The simulation is based on an emulator developed by Python Matplotlib.The map is a 10 x 10 cartesian coordinate. All the obstacles are appropriately deployed to ensure that the local minima exist while maintaining the map's complexity. The obstacle deployment is shown in figure 6.0. The start position is (0,0) and is represented in a red hexagon. The goal position is (10,10) and is represented in a red star.



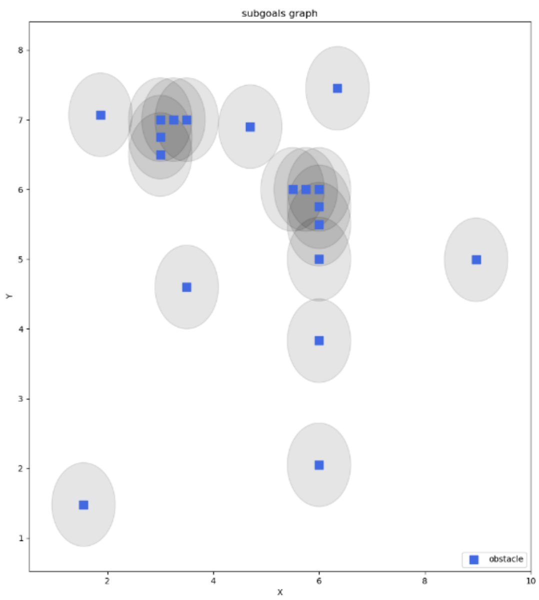


Figure 6.0

When using the original APF method (figure 6.1 (a)), the robot will get stuck at the local minimum of a right-angled shape obstacle, the APF+SA (figure 6.1 (b)) help the robot escape from the local minima, but the path it generated is very inefficient and lengthy. Our proposed approach (figure 6.1 (c)) can avoid the local minima and generate a smooth path shorter than the APF+SA path. Note that in figure 6.1 (c), the green translucent stars represent the initial sub-goals, indicating the robot has been stuck here before. The red translucent stars represent the last sub-goals list that guides the robot to escape the minimum, and it does not get stuck after that.

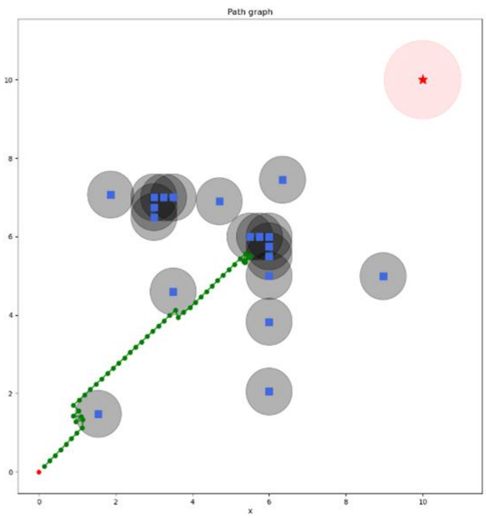


figure 6.1 (a) APF

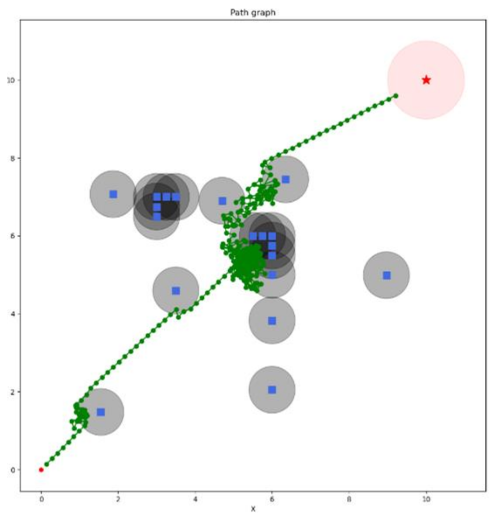


figure 6.1 (b) APF + SA

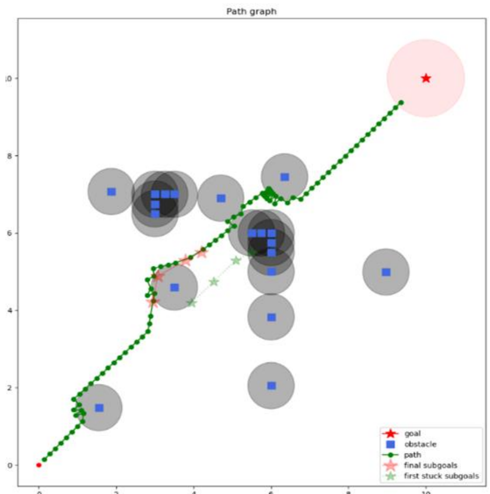


figure 6.1 (c) APF +VNS

figure 6.1 result I

In conclusion, i) Our approach can achieve the local minima avoidance and finally reach the goal, ii) And the path it generated is shorter than the path generated by using SA. It is also more efficient and smooth, iii) Theoretically, the path can be a suboptimal solution if the parameter set and coefficients are selected appropriately. This is because of the VNS algorithm, which can produce a global optimum solution concerning all neighbourhoods.

Experiment II: different combinations of neighbourhood

This is derived research about measuring the performance of using the different combination of neighbourhoods. We evaluate the following neighbourhood configurations:

- $C_{\text{rand-only}}$: [random-eight, random]
- $C_{\text{4-dir}}$: [up, right, left, down]
- $C_{\text{4-dir-obsFree}}$: [up, right, left, down, obs-free]
- $C_{\text{local-opz}}$: [all the local path optimization neighbourhoods]
- C_{all} : [four direction + local path optimization + random]

Moreover, each neighbourhood combination score is the number of sub-goals that have been used and failed to escape from the local minima (see figure 3, the right subgraph shows these sub-goals). The higher the score, the less efficient the combination is. If only two to five sub-goals, then this combination is considered an optimal one.

When only using the $C_{\text{rand-only}}$ combination (figure 6.2 (a)), the performance is very bad and it fails to reach the goal, and the score is very large. $C_{\text{4-dir}}$ (figure 6.2 (b)) does better it can reach the goal, note that his combiantion only allows the subgoals moving four directions, so there are a lot of Parallel trajectories in the sub-goals graph (figure 6.2 (b) right side). $C_{\text{4-dir-obsFree}}$ (figure 6.2 (c)) has the obs-free brughbourhood, so all the subgoals keep away form the obstacles. $C_{\text{local-opz}}$ (figure 6.2 (d)) includes the powerful local path optimization neighbourhoods therefore it uses less than 5 subgoal lists to reach the goal. At last, C_{all} (figure 6.2 (e)) also uses less than 5 subgoal lists to reach the goal.

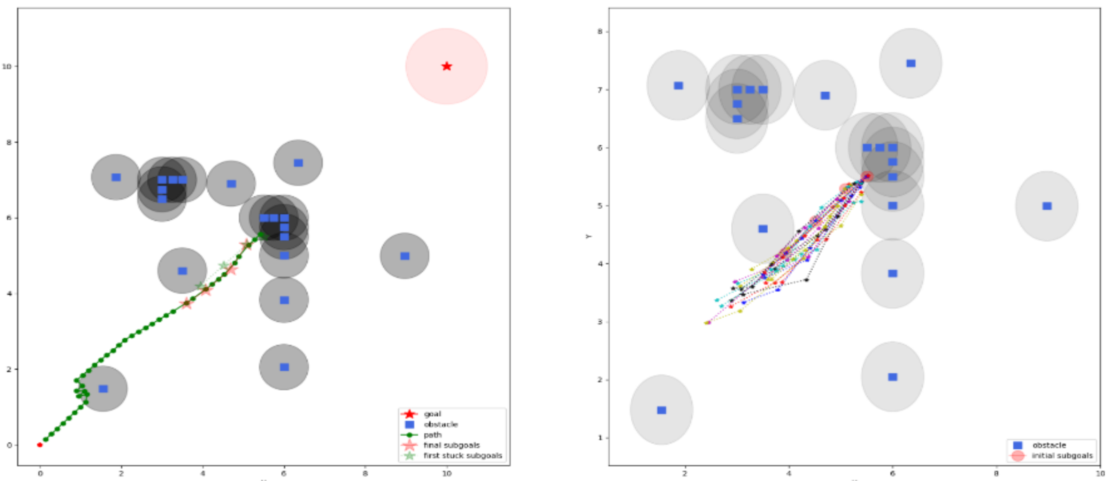


figure 6.2 (a) $C_{\text{rand-only}}$

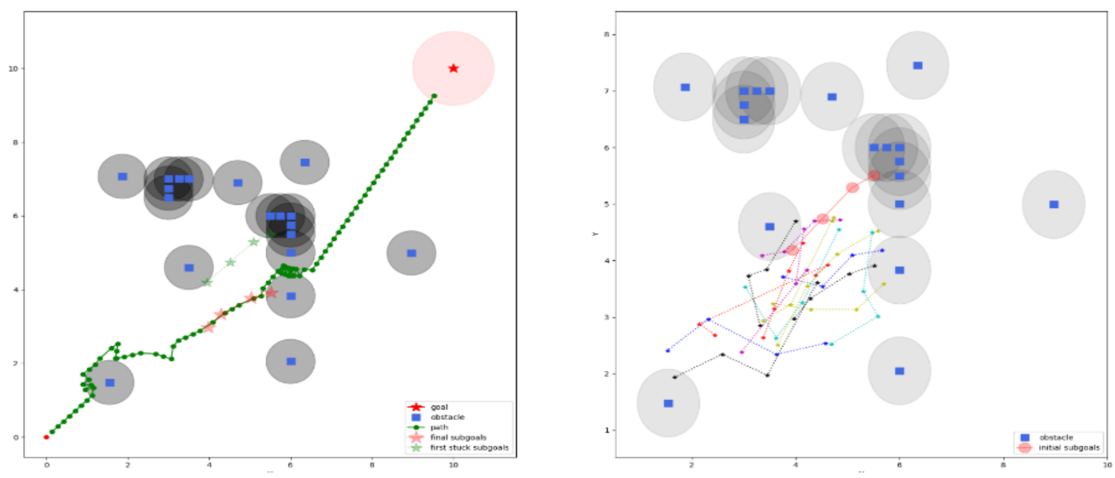


figure 6.2 (b) C4-dir

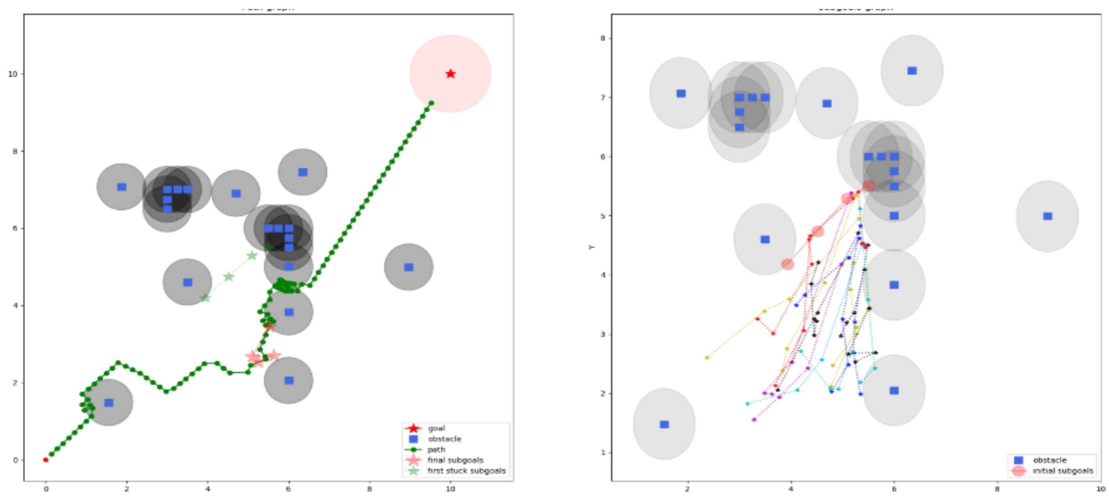


figure 6.2 (c) C4-dir-obsFree

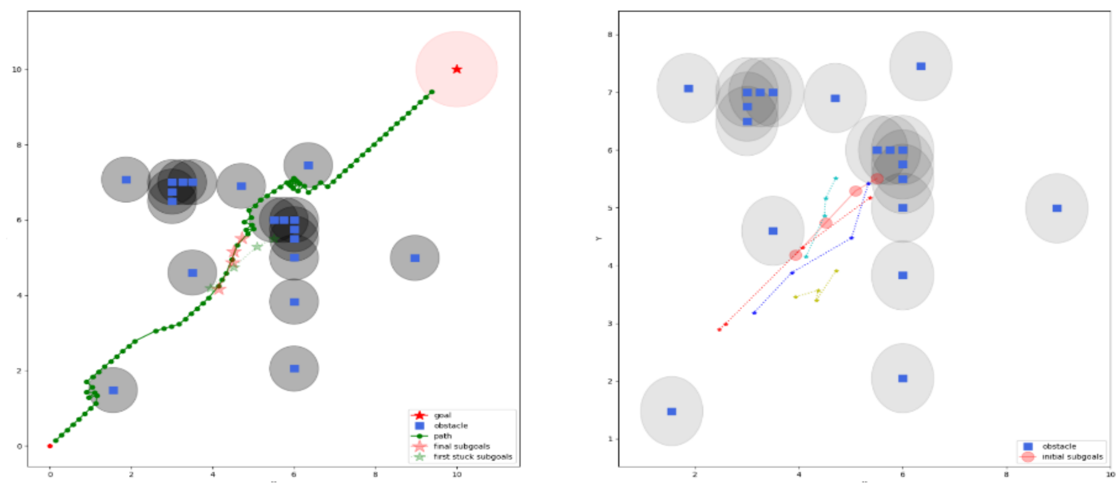
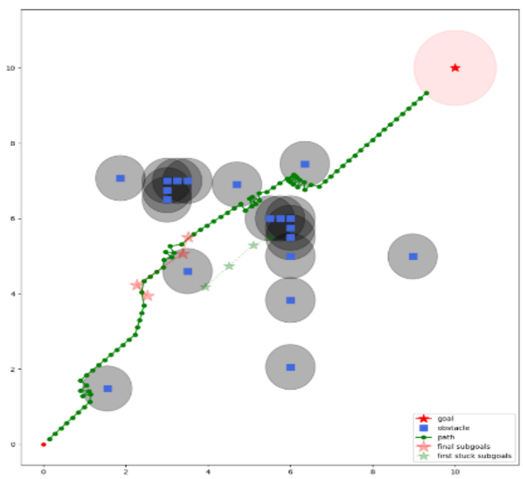


figure 6.2 (d) Clocal-opz



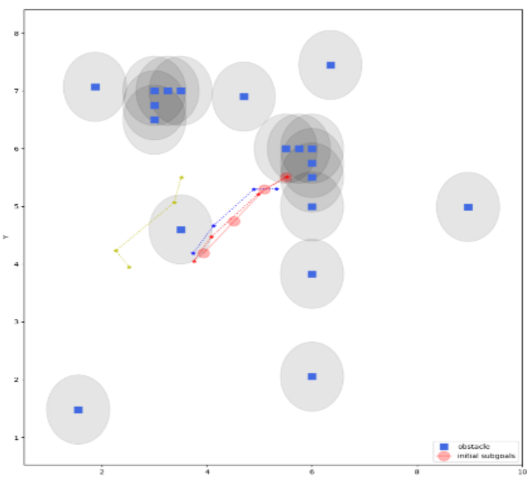


figure 6.2 (e) C_{all}

Figure 6.2: result II

	Escape from the LM?	Score	Path length
$C_{rand\text{-}only}$	No	50+	None
$C_{4\text{-}dir}$	Yes	14.6324	27.143
$C_{4\text{-}dir\text{-}obsFree}$	Yes	23.4556	19.562
$C_{local\text{-}opz}$	Yes	3.73	16.145
C_{all}	Yes	3.41	15.084

Tabular 1

From the tabular 1, we can conclude that, i) $C_{local\text{-}opz}$ and C_{all} are the best because of the local optimization neighbourhood, ii) $C_{4\text{-}dir}$ can achieve the LMA but require more time, iii) the random neighbourhoods cannot achieve the goal because of the lack of heuristic. Path length of $C_{local\text{-}opz}$ and C_{all} are very short and it is close to the shortest path length:

$$optiaml\ path\ length = 10 \cdot \sqrt{2} = 14.14214.$$

Question 7

From our perspectives, the traditional path planning algorithm could not recycle the historical experience data and use the data for training and learning. It is the same situation as the APF method. Though our improvement by applying the VNS algorithm into the APF method to solve local minima encountered, the Goal non-reachable problem, the low accuracy and efficiency of the algorithm remain. From the aspect of the VNS algorithm, it uses “neighbours” to replace the generate escaping path. However, the basic framework of this algorithm is using randomization. As a result of this, the path generated each time is also randomized, the same as the length. Thus, applying techniques such as Deep reinforcement learning approaches, which uses neural network structure for online data training and historical data recycling and storing, are necessary. Since these techniques could make the algorithm learn from the previous experience, and this learning and recycling process could improve the planning accuracy. For the next step of the research, combining our VNS-APF algorithm with the RL algorithm would be the future. Furthermore, the actual verification of the real environment should be considered. Thus, considering the motion model planning in a complex, realistic environment and then verifying it could be the focus of the next research.

Question 8

This project helps show how to implement a path planning algorithm and improve it. When designing the framework of the algorithm, we spent much time on how the individual pieces of the functions should be constructed. After implementing the functioning part, the result of the current algorithm is not good at all. Therefore, we designed new path planning subgoals and tested the experiment data. Through the testing part, we learned a lot about how important the accuracy and efficiency of each algorithm are. The project also taught us the importance of choosing improvement approaches and testing the data set.

To sum up, from this experience, we think we should have more horizontal planning of this improvement project. We focused on avoiding local minima while the general efficiency, accuracy, and application of this algorithm into a virtual environment are not considered. During the last period of this project, after analyzing the VNS-APF algorithm, we do not have enough time for further improvement. Thus, planning different subgoals of the project and setting a periodical check on the progress should have been conducted. Additionally, from this research project, we realized a formal research project is of tremendous workload. Therefore, teamwork and cooperation are of great importance throughout the research process, though we did well in team meetings and task distribution.

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