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Improved PRM for Path Planning in Narrow Passages

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***Abstract* - In view of the shortcomings of Probabilistic Roadmaps (PRM) in the case of narrow passages, an improved method based on optimal sampling strategy is proposed. By sampling the dense area of the obstacles, the sampling points distributed inside the obstacle are selected and uniformly sampled by the distanced, so that the sampling point is generated around the obstacle in the free area, thereby increasing the number of sampling points in the narrow passages. The simulation results show that the improved PRM has more sampling points in the narrow passages than the standard PRM. And the time of path planning, the success rate and the path length are also significantly improved.**

***Index Terms* –path planning, PRM, sampling strategy, narrow passage.**

I. Introduction

In the research of autonomous mobile robots, path planning as a core part has been extensively studied by researchers. Path planning is a path that to connect the starting point and the ending position according to a certain characteristic (time, distance), so that the path and the obstacle maintain a relatively safe distance, meanwhile ensure that the path length and planning time are as short as possible [1]. Therefore, variety of path planning methods such as artificial potential field, Probabilistic Roadmaps (PRM), Rapidly-exploring Random Trees (RRT), Ant Colony Optimization (ACO), Artificial Potential Field (APF) and Genetic Algorithm (GA) [2-7]. However, most algorithms such as APF, ACO and GA need to accurately model the environment map and most of the obstacles must be regular graphics. In practice, the environment is usually complicated, and the obstacle shape uncertainty factor is too high, so the model is difficult and computationally intensive, making it difficult to apply. However, the PRM are based on random sampling and have probability completeness. They're good at dealing with high-uncertainty and high-dimensional maps, so they have been widely used in practice.

The PRM randomly samples the free space and connects the sample points to construct a path map. However, because of the probability property of the sampling strategy of the PRM, the sampling probability of each region in the map is the same. Therefore, when the number of sampling points is constant, the larger the area of the free area, the more sampling points. However, it is difficult to ensure that there are enough multiple sampling points in the narrow passages area of the map. Therefore, it is very important to identify narrow channels in real time and effectively improve the sampling points. By establishing the probability model of map obstacles and analyzing and predicting the model to detect obstacles and narrow channels, the number of sampling points in these areas can be effectively increased. Reference [8] was proposed the Narrow Passage Predictive model (NPP) for path planner in dynamic environment. The predictive model is obtained by the famous classification method of Support Vector Machine (SVM), considering the real-time change of map environment obstacles, time factors and spatial information are introduced during the establishment of the model. And the obtained map probability model can be used to detect the position of the narrow passage, thereby increasing the number of sampling points in the narrow passage. Reference [9] was proposed a Long Short Term Memory (LSTM) Model, by predicting the obstacle position, the obstacle trajectory is divided into time series, and the position estimation at the next time is brought into the state validity test of the planning algorithm to generate an optimal path. The prediction of obstacle model can reduce the time of traversing and reprogramming, and the number of sampling points in narrow channel can also be increased by optimizing the sampling stage. In view of this situation, Boor proposed Gaussian sampling method [10], Gaussian sampling is based on the density of obstacles, which makes the sampling points of obstacle areas dense, thus forming a reasonable path map. Hsu proposed a bridge test method, which randomly extracts two points from in the obstacle and connects two points [11]. If the midpoint of the two points is in the free area, the point will be extracted. This point is taken in a narrow passage, which greatly increases the number of sampling points in the narrow passages. However, both Gaussian sampling and bridge test method are applicable to areas where obstacles exist, planning efficiency is greatly low when areas far from obstacles, even paths are not planned. Reference [12] was proposed an adaptive sampling method, this method that combines the probability likelihood function and Gaussian sampling to greatly increase the sampling points falling in a narrow space, thus improving the use of the PRM in practical uncertain environments. However, it does not focus on the in-depth study of the path planning of narrow passages. An improved PRM is proposed, which introduces an artificial potential field method in the learning stage, so that the point falling within the obstacle moves from the obstacle to the free space by the repulsive force of the obstacle, increasing the sampling points in the narrow passages [13]. But it is difficult to determine the value of the potential field force when it is used in practice, and the results of different potential field forces are also very different. A hybrid path planning technology based on Harmonic Function (HF) and Probabilistic Roadmap (PRM) is proposed [14], this approach uses fluid dynamics to build a probabilistic road map and uses Fluid Dynamic (FD) to identify narrow channels, thereby increasing connectivity in narrow channels. the method better than each individual in terms of finding a collision free path in environments where narrow passages exist, but it greatly increases the complexity of the algorithm. After finding a feasible path, the planning results in the narrow channel are usually not smooth, so the path needs to be optimized. Reference [15] was proposed a time-optimal trajectory planning method based on quintic Pythagorean-Hodograph (PH) curves, which can be used not only in robot motion control, but also in path planning to make the robot's path smoother and smoother.

In this paper, the PRM is improved in dealing with the shortcomings of sampling points in narrow passages. The sampling strategy of PRM is improved. Firstly, the free area is sampled and a certain number of sampling points are taken. Secondly, based on the obstacle sampling, the main idea of the method is taking a point in the obstacle, and then perform uniform sampling again within a certain range d of the sampling point. If the sampling is in the free area, the point is retained and vice versa. Finally, the sampling points are generated around the obstacles, and there are enough sampling points in the local map to plan a reasonable path. This paper is divided into four sections. The first section introduces the basic principles and deficiencies of the PRM. The second section introduces the principles and steps of an improved PRM based on an optimized sampling strategy. In the third section, the improved PRM is simulated, compared with other algorithms, and the results are analyzed. The fourth section summarizes the improved algorithm.

II. Probabilistic Roadmaps

A. Basic principle of PRM

The basic idea of the PRM is to use a probability map to represent the free space of the environment in which the mobile robot is located, and then to find the optimal path by constructing a route network map. The algorithm can be completed in two phases, namely the preprocessing phase and the query phase. The principle steps of the PRM path planning are as follows:

1. Preprocessing phase: Uniform sampling of the environmental map using uniform distribution in free space to construct a sampling point map. Then connect the various points to construct a path network diagram. As shown Fig. 1. The preprocessing phase can be divided into two phases:

(1) Sampling in the map, if the sampling point is in the free area, the point is adopted, otherwise the point is discarded, and finally the sampling map is constructed.

(2) Establish an undirected path network diagram $R=(N,E)$, where N denotes a random number of points (set of points) and E denotes a path between all possible two points.

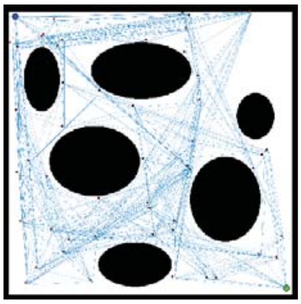


Fig. 1 Preprocessing phase

2. Query phase: query the path from a starting point to an ending point. As shown Fig. 2

In the query phase, using the undirected path network map that has been constructed in the preprocessing phase $R=(N,E)$, it is only necessary to select an appropriate path in the undirected path network map according to the set starting point (s) and the target point (g). The A* heuristic algorithm is used in the query phase to ensure that a reasonable path is found in the network graph.

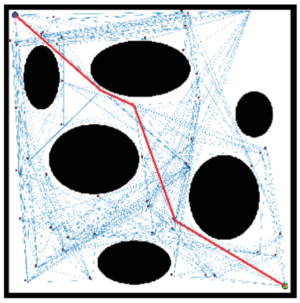


Fig. 2 Query phase

B. Defects of the PRM

The number of sampling points and the position of the sampling point of the PRM can determine the construction of the entire path map and the planning of the final path in the query phase. In the preprocessing phase, the PRM usually uses a uniform distribution for sampling, to ensure that each free space of the global map has sampling points, and it is possible to plan a reasonable path at the greatest possible extent. However, when there is a narrow path in the local map, and the optimal path needs to pass through the narrow passages, uniform sampling is very inapplicable. The sampling probability is equal everywhere in the entire map space, and the number of sampling points is proportional to the size of the space. The narrow passage does not have enough sampling points compared to other areas. Therefore, when constructing the roadmap, the narrow passages does not have an optimal path because there are not enough sampling points.

In Fig. 3, when 50 sampling points are taken in the preprocessing phase, there are too few sampling points in the narrow passages. Therefore, in the query phase, the route map through the narrow passages cannot be constructed because there are too few sampling points in the narrow passages. So that no optimal path can be constructed.

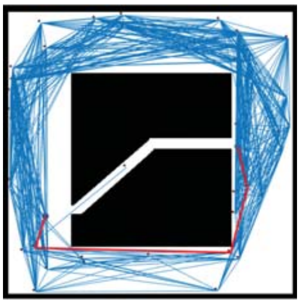


Fig. 3 Standard PRM with 50 sampling points

However, when the sampling point is sufficient, the standard PRM can overcome the problem. Because with the increase of the overall sampling point, enough sampling points can be obtained in the narrow passages, and the optimal path can be planned. The result is shown in Fig. 4.

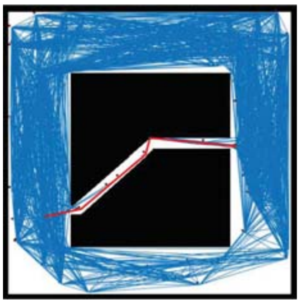


Fig. 4 Standard PRM with 200 sampling points

The results of different number of sampling points of the standard PRM are shown in Table I. When the number of sampling points is sufficient, the path can be planned in the narrow passages. However, when there are too many sampling points, it takes a lot of time to construct the path map and the query path in the query phase, which will greatly reduce the running efficiency of the PRM. Therefore, we need a method to sample according to the narrow passage, and at the same time ensure the efficiency of the PRM.

TABLE I
RESULTS OF DIFFERENT SAMPLING POINTS OF THE STANDARD PRM

Sampling Points	Time (s)	Number of nodes in a narrow passage
50	0.5	1
200	2.3	6

III. IMPROVED PROBABILISTIC ROADMAPS

A. *Improved method based on optimized sampling strategy*

The standard PRM uses a uniform distribution for sampling, because of the probability of uniform sampling and the like, the region with a large blank area in the map has a higher probability of acquiring sampling points, so the sampling points in the narrow passages where the obstacles are concentrated are usually It is difficult to take, but sample points located in or near the obstacle area can be used to connect the ends of the narrow passages. Therefore, I hope to take the point near the obstacle. This paper divides the sampling method into the following two steps: 1) adaptive random sampling in the environment map; 2) sampling in the obstacle area, selecting sampling points in the obstacle, Uniform sampling is performed within a certain range of the point until it falls to the free area. The specific process is as follows:

Firstly, adaptive random sampling is used in the map. In order to overcome the shortcomings of the standard PRM, there are a large number of sampling points in the blank area of the sampling stage, while the narrow passages area has relatively few sampling points. In this paper, the density of the obstacles is used for adaptive sampling. A large number of samples are taken in the dense area of the obstacle, while relatively dispersed sampling points in a large area of idle area. The number of sampling points is proportional to the density of the obstacle.

The second step continues sampling in the obstacle area in order to increase the point in the narrow passages. The sampling point in Fig. 5 is located in the obstacle, such as point *b*, and a circular area having a radius *d* is constructed around the point, and uniform sampling is performed in the area. If the point taken is in a free area, such as point c, then the point is taken. If it is inside an obstacle, such as point e, discard the point and continue sampling. This ensures that there are a large number of sampling points in the obstacle area or in the narrow passages.

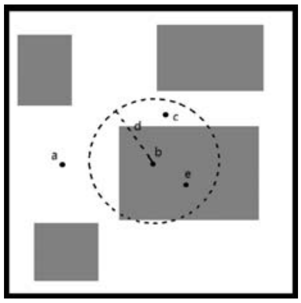


Fig. 5 Sampling strategy

B. *Dynamic sampling distance*

The distance *d* is dynamically selected according to the size of the map and the complexity of the obstacle. When the value of *d* is large, the sampling points taken are far away from the obstacle to a large extent, which affects the planning efficiency. When *d* is selected too small, the probability that there is no free area in the range is greatly increased, so frequent re-sampling within the obstacle is required, so that the running time of the algorithm is increased. Therefore, a reasonable distance *d* can further improve the operational efficiency of the improved algorithm to a certain extent. In this paper, *D* is taken dynamically, and the minimum distance d_{min} is set beforehand. When the points in the range are not taken to the free area, the d_{min} is doubled until the points in the range are located in the free space.

The improved PRM is improved in the preprocessing phase, and the adaptive sampling with higher flexibility is adopted. The basic steps of the sampling strategy are as follows:

Steps to improve the sampling strategy of the PRM:
Repeat
    $c \leftarrow C$ Randomly sample a bit according to the density of obstacles in the map space
    Take $d=d_{min}$;
    If $c \leftarrow C_{free}$ in the free area
    $V \leftarrow V \cup \{c\}$ adds point c to the graph node set;
    Else
    In the range where the point c is the centre d, the uniform sampling takes the $c1$ point;
        If $c1$ is inside the obstacle
            Take $d=d*2$ and resample with d as the range;
        Else
            $V \leftarrow V \cup \{c1\}$ adds point $c1$ to the graph node set;
Until the condition is terminated

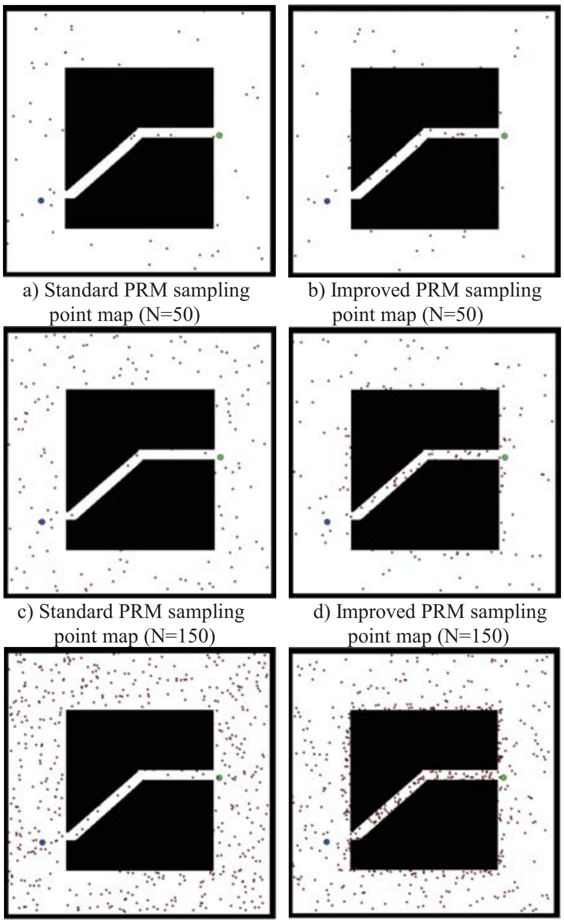
IV. SIMULATION

In order to verify whether the improved algorithm is effective and improve the processing ability of narrow passages, this paper simulates the sampling stage of the improved algorithm and the overall algorithm planning efficiency under Matlab2018a. The sampling phase simulation is to verify whether the number of sample points in the narrow passages is improved by the improved algorithm. The overall planning efficiency simulation is mainly carried out in terms of planning success rate, planning time and path length, and whether the improved algorithm has obvious changes in these three aspects. In order to better illustrate the improved algorithm's ability to handle narrow passages. The simulation is carried out using a map with a large area of free area and a narrow passage, where the blue point represents the starting point and the green represents the end point.

A. Improved PRM sampling stage algorithm

The improved PRM is mainly reflected in the improvement of the sampling strategy. In order to verify the change of the sampling points in the narrow passages of the improved PRM during the sampling phase, the improved PRM is compared with the standard PRM to take the same sampling point. The simulation result is shown in Fig. 6. The improved PRM has higher density of sampling points in the obstacle area than the standard PRM, and also has more sampling points in the narrow passages.

In order to better verify the application of the improved algorithm in the narrow passages problem, this paper repeats 50 experiments in the case of sampling points of 50, 150, 500, respectively, and counts the number of nodes in each narrow passage. The average is compared and the final result is shown in Table II.



a) Standard PRM sampling point map (N=50)   b) Improved PRM sampling point map (N=50)
c) Standard PRM sampling point map (N=150)   d) Improved PRM sampling point map (N=150)
e) Standard PRM sampling point map (N=500)   f) Improved PRM sampling point map (N=500)

Fig. 6 Algorithm optimization before and after the sampling phase

TABLE II
NUMBER OF SAMPLING POINTS IN NARROW PASSAGES UNDER DIFFERENT SAMPLING POINTS BEFORE AND AFTER IMPROVEMENT

Sampling point	(Standard) the average number of nodes in a narrow passage	(Improved) the average number of nodes in a narrow passage
50	5（±2）	11（±2）
150	7（±8）	24（±4）
500	12（±9）	90（±8）

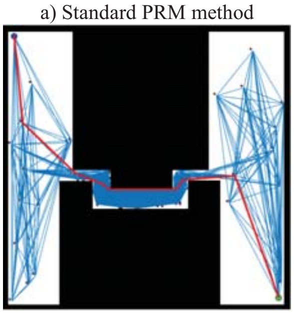
In Fig. 6 and Table II, the improved PRM has better adaptability and applicability than the standard PRM in processing narrow passages. In the case of the same number of sampling points, the improved PRM has more sampling points in the narrow passages than the standard PRM, so that the PRM can plan the path in the narrow passages, and the number of sampling point's increases. More, the advantages are more obvious. According to the simulation results, the improved PRM can effectively compensate for the shortcomings of the standard PRM in narrow passages.

B. Improved PRM path planning efficiency analysis

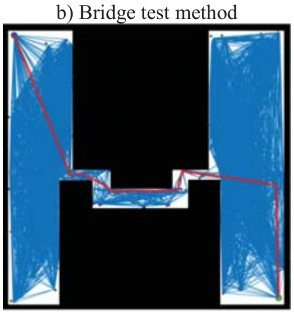
The improved PRM can effectively take appropriate sampling points in the sampling stage, so that the PRM has strong adaptability when encountering narrow passages. In this paper, the efficiency of PRM planning, planning time and path length are analyzed. The standard PRM, bridge test method and improved PRM are simulated respectively. For each method, the sampling point is 150. The simulation is carried out, and the running result is shown in Fig. 7(a) is the standard PRM. From the running result, the standard PRM cannot plan the path in the case of 150 sampling points. Fig. 7(b) shows the bridge test method. The bridge test method can plan the path because there are a large number of sampling points in the narrow passages. But there are too many sampling points in the narrow passages and too few sampling points in the large free area, so that the planning time and the path length is not optimal. Fig. 7(c) shows the improved PRM. The improved PRM also has enough sampling points in the narrow passages to plan the path. From the result graph, the improved PRM can effectively plan in the narrow map passages path.

In order to verify the efficiency of improved algorithm, the algorithm simulation was carried out in the narrow passage obstacle map of Fig. 7, and each simulation sampling point was taken as 150, and 50 repeated experiments were performed for each algorithm. The simulation experiment results are shown in Table III.

a) Standard PRM method



b) Bridge test method



c) Improved PRM

Fig. 7 Three algorithms narrow passages simulation results

TABLE III
COMPARISON RESULTS OF THREE ALGORITHMS

Algorithm	Success rate (%)	Average planning time (s)	Average path (m)
Standard PRM	25.8	4.66(±1.5)	821.89(±10)
Bridge Test	90	3.52(±2)	834.14(±11)
Improved PRM	98	3.21(±1)	816.11(±8)

It can be seen from Fig. 8 and Table III that the improved PRM has higher practicability than other algorithms when dealing with the narrow passages problem. The success rate of standard PRM is very low. After the experimental comparison, the improved PRM succeeds in the map with narrow passages. The rate has a higher success rate than the other two algorithms. In terms of planning time, the improved PRM has a faster planning speed than the standard PRM and the bridge test method, and the improved PRM in terms of the planned path length. There are shorter paths than the other two algorithms. After repeated experiments, the improved PRM has a large improvement in success rate and path length, and the overall planning efficiency has been significantly improved.

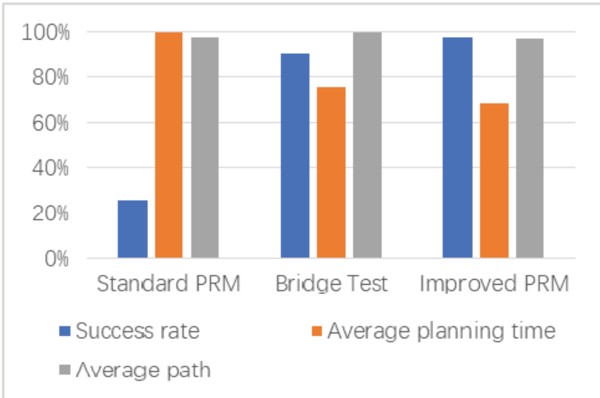


Fig. 8 Comparison Results (The success rate is the ratio of 100 experiments, Average time ratio to maximum Tim, The ratio of the average length to the maximum length)

V. CONCLUSION

In order to solve the shortcomings of PRM in dealing with narrow passage, an improved PRM is proposed in this paper. By optimizing the sampling strategy of standard PRM, the number of sampling points in narrow passage is increased. It makes the algorithm have better adaptability when it encounters narrow passage. Finally, the standard PRM method, bridge test method and improved PRM are simulated in different scenarios. The simulation results show that the improved PRM not only has a higher success rate in narrow passage, but also has better execution time and path length than other methods, and has effectiveness and stability.

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REFERENCES

[1] Pol, Rahul Shivaji, and M. Murugan, "A review on indoor human aware autonomous mobile robot navigation through a dynamic environment survey of different path planning algorithm and methods," *IEEE International Conference on Industrial Instrumentation and Control (ICIC)*, pp. 1339-1344, May 2015.

[2] Chen, Yong-bo, et al, "UAV path planning using artificial potential field method updated by optimal control theory," *International Journal of Systems Science*, vol. 47, no. 6, pp. 1407-1420, June 2014.

[3] Kavraki, Lydia, and J-C. Latombe, "Randomized preprocessing of configuration for fast path planning," *IEEE International Conference on Robotics and Automation*, May 1994.

[4] Strandberg,Morten, "Augmenting RRT-planners with local trees," *IEEE International Conference on Robotics and Automation*, vol. 4, pp. 3258-3262, April 2004.

[5] Pérez-Higueras, Noé, Fernando Caballero, and Luis Merino, "Teaching robot navigation behaviors to optimal RRT planners," *International Journal of Social Robotics*, vol. 10, no. 2, pp. 235-249, April 2018.

[6] Uriol, Ronald, and Antonio Moran, "Mobile robot path planning in complex environments using ant colony optimization algorithm," *2017 3rd international conference on control, automation and robotics (ICCAR)*, pp. 15-21, April 2017.

[7] Liu, Zhendong, Yawei Kong, and Bin Su, "An improved genetic algorithm based on the shortest path problem," *IEEE International Conference on Information and Automation (ICIA)*, pp. 328-332, August 2016.

[8] Liu, Hong, Fang Xiao, and Can Wang, "A predictive model for narrow passage path planner by using Support Vector Machine in changing environments," *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 2991-2996, May 2015.

[9] Todi, Vasudha, Gunjan Sengupta, and Sourangshu Bhattacharya, "Probabilistic Path Planning using Obstacle Trajectory Prediction," *Proceedings of the ACM India Joint International Conference on Data Science and Management of Data*, pp. 36-43, January 2019.

[10] Boor, Valérie, Mark H. Overmars, and A. Frank Van Der Stappen, "The Gaussian sampling strategy for probabilistic roadmap planners," *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 1018-1023, May 1999.

[11] Hsu, David, et al, "The bridge test for sampling narrow passages with probabilistic roadmap planners," *IEEE International Conference on Robotics and Automation (ICRA)*, vol. 3, pp. 4420-4426, September 2003.

[12] Missiuro, Patrycja E, and Nicholas Roy, "Adapting probabilistic roadmaps to handle uncertain maps," *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 1261-1267, May 2006.

[13] Aarno, Daniel, Danica Kragic, and Henrik I. Christensen, "Artificial potential biased probabilistic roadmap method," *IEEE International Conference on Robotics and Automation (ICRA)*, vol. 1, pp. 461-466, April 2004.

[14] Kazemi, Moslem, Mehran Mehrandezh, and Kamal Gupta, "An incremental harmonic function-based probabilistic roadmap approach to robot path planning," *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 2136-2141, April 2005.

[15] Su, Tingting, et al, "Time-optimal trajectory planning for Delta robot based on quintic pythagorean-hodograph curves," *IEEE Access*, vol. 6, pp .28530-28539, April 2018.