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Dynamic RRT* Algorithm for Probabilistic Path Prediction in Dynamic Environment

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Abstract*:* In the recent years, the probabilistic path planning is an emerging area in the field of navigation. The navigation applications increases day by day which helps the society to solve the real world problems. The major challenge in this path planning is to deal with the dynamics in the environment. The dynamicity refers with the ability of an obstacle to move around the working environment and able to change their possessions frequently. There are many solutions were available to deal with the challenges in the dynamic environment and support the robot to navigate over the environment to move from source to a destination. Sampling based algorithms are the one which are most suitable for the path planning where the dynamic obstacles are present in the working environment. Rapidly Exploring Random Tree (RRT) and their variants like RRT*, F-RRT*, PQ-RRT*, etc. are the algorithms, have been shown significant improvement over predicted path and the time to navigate over predicted path. These variants of RRT* algorithms are analyzing over the asymptotic behaviour and the cost of the generated path is also analyzed. In this work we have proposed a dynamic RRT* algorithm which is critically analyzed in terms of optimality and the asymptotic behaviour is cortically analyzed to present a dynamic RRT* planner, which can be effectively used for the path planning over dynamic environment. However these algorithms were not analyzed in terms of dynamicity of the environment and make the approach dynamic which can adapt the environment features to be work dynamically to generate a path. The presented simulation results shows that the presented dynamic RRT* algorithm work significantly better in terms of path length and the navigation time during the actual run from source to a destination. The study of path planners developed over the years by the research community has been discussed and presented here in this work. Moreover the proposed dynamic RRT* approach shows that the computational cost of the algorithm makes it to a probabilistically complete solution to work with the dynamic environment.

Keywords: *Dynamic, Path Planning, RRT*, Environment, algorithm.*

1. Introduction

There are a variety of real-world applications for mobile robots or other intelligent devices today, including those in the domains of medicine, agriculture, science, business, engineering, industries, defense, transportation, and others. Due to the increasing usage of mobile robots in both industrial and everyday life, motion planning for robots has been a hot topic, particularly in the last few years. Also the path finding techniques and obstacle avoidance is key point while discussing the various navigational applications. With the need of next generation devices and application there is a need of continuous improvement in the existing state of art path planning techniques to meet the need of current and future requirements with the help of currently available techniques. A robot motion planning is complex task, which needs significant knowledge of robot dynamics and a mathematical model to predict the path for the navigation of mobile robot. There are several issues in Robotic path planning, some of them like Representation and presentation of working environment; Design of working environment and placement of obstacles in the environment; Identification of static and the dynamic environment; Motion identification of the obstacles; Trajectory computation of the obstacles; design collision detection mechanism; design collision avoidance mechanism; integrate collision detection and avoidance mechanism with probabilistic path planner. The research community has presented various solutions for the mobile robot path planning. In which the most popular ne is the sampling based approach due to its dynamic behavior and the adaptation to the constrains of the environment which is likely to be as a dynamic behavior of the environment. The most common sampling based approach is the Rapidly exploring random tree (RRT) which works well for the path generation for the mobile robot in the dynamic environment. So, now a days most of the path planning solution is presented using RRT as a

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base algorithm and the computation cost, path length, time to navigate and the asymptotic behavior is challenged by the research community and the best possible results and the solutions is get communicated and presented by the researchers. However design a system to estimate future location of obstacle based on its trajectory information, supported by the function for trajectory prediction, collision detection to generate a probabilistic path for the navigation from source to destination in order to reduce the navigation time is expected from the path planning solutions.

2. Literature Survey

The artificial potential field (E. Rimon E. et al., 1992) and fuctional neural network based architecture (Panagiotopoulos D. et al., 1999) is one the oldest technique for mobile robot path planning, which is most suitable for static environment. The static environment has a least constraints to deal with as all the obstacles are static in nature. The New potential fields (Ge S. et al., 2000), sampling based approaches (Plaku E. et al., 2004), are the approaches which are suitable for path planning in the dynamic environment. These approaches are providing a probabilistic path for the mobile robot navigation with significantly higher navigation time due to some amount of collision in the real run and the length of path of longer than the desired. The most popular method used in this approach graph, known as probabilistic road maps (Al-Hmouz R., 2004) and (Baumann M. et al., 2010), is constructed by randomly choosing a pedestrian going through traffic with their random current state. This algorithm and a derivative of it have been used to create graphs that resemble road maps and depict collision-free paths. They also compute the shortest path between various connecting nodes in the graph, from source to destination, by using a multiple-query approach. It was noticed that while multiple samples had been developed using various roadmaps and that it was probabilistically finished with zero delay error, it had the drawback of only working on electronic robots and not performing as well in real-world situations. In order to reduce the navigation time, the EET planner (Rickert M. et al., 2014) and Effective motion planner (Ma L. et al., 2015) has been proposed with significant improvement in the path length and the navigation time. These planners are affected by the signal artifacts, and disturbances and having Inaccurate terminal state, and the slow exploration, that makes the scope of improvement in this planner. The Particle Filter Based method (Zhao B. et al., 2014) and (Wang B. et al., 2016), which can diagnose faults effectively, and can provide good state estimation and it is easily implemented. But, the approach is Affected by signal artifacts, and disturbances which may affect the predicted path length. To improve the accuracy of path planning Rapidly Exploring Random Tree (RRT) (Ju T. et al., 2014) Algorithm and a improved version Rapidly Exploring Random Tree (RRT*) Algorithm (Pharpatara P. et al., 2017) is introduce to provide efficient motion planning. These Rapidly Exploring Random Tree’s are effective in providing collision free path but the path look weird and disturbed it will take longer distance from initial point to the goal point. To overcome the challenges of Rapidly Exploring Random Tree’s, the improved versions has been presented by the may researcher’s which are Parellel-RRT* (Ichnowski J. et al., 2018), Multidimensional-RRT* (R. Cui R. et al., 2018), RL-RRT* (Chiang H. et al., 2019),etc. but these algorithms can be challenged in terms of Path length, No. of collision during the navigation, navigation time, time complexity and space complexity.

Sr. No	**Author**	**Methodology/ Approach**	**Pros**	**Corns**
1	E. Rimon E. et al., **1992**	Artificial Potential Field	Easy to implement, Effective over static environment	Less effective over dynamic environment
2	Panagiotopoulos D. et al., **1999**	Functional Neural Network Architecture	Works on interactive environment, Useful for autonomous mobile robots	Need security mechanism
3	Ge S. et al., **2000**	New Potential Functions	Can be used for dynamic environment	Convergence rate is very low
4	Plaku E. et al., **2004**	Sampling Based MMQP	Useful for multiple-query motion planning, It can be efficiently parallelized, More decoupled	Less effective for low dimensional space, Complex data structure

5	Al-Hmouz R., **2004**	PRM*(Probabilistic Road Maps (PRMs)	Excellent performance in higher dimension state space, It constructs graph with extensive set of obstacle(collision free) trajectories.	1.Need more computation time to construct a graph 2. Need more storage space.
6	Baumann M. et al., **2010**	PRM*(Probabilistic Road Maps (PRMs)	Excellent performance in higher dimension state space, It constructs graph with extensive set of obstacle(collision free) trajectories.	1.Need more computation time to construct a graph 2. Need more storage space.
7	P. Cheng P. et al., **2008**	PRM-based sampling-based algorithms	Effective in c constraint based environment	Not effective under unsupervised environment
8	Rickert M. et al., **2014**	EET Planner	High Computational Efficiency, Effective over sampling based planners	inherent structure, the planner's sampler
9	Ma L. et al., **2015**	EMP (Effective motion planner)	Effective in a realistic setting for on-road autonomy and route planning	insufficient exploration speed and inaccurate terminal state
10	Zhao B. et al., **2014**	Particle Filter Based method	robust, capable of fault diagnosis, capable of providing good state estimation, and simple to implement	Affected by signal artefacts, and disturbances
11	Wang B. et al., **2016**	Particle Filter Based method	robust, capable of fault diagnosis, capable of providing good state estimation, and simple to implement	Affected by signal artefacts, and disturbances
12	Ju T. et al., **2014**	Rapidly Exploring Random Tree Algorithm (RRT)-Designed to solve non homonymic constraints.	Provides high degree of freedom, Random Selection give more easy handling of structure.	Random Data Structure.
13	Véras L. et al., **2019**	Rapidly Exploring Random Tree Algorithm (RRT)-Designed to solve non homonymic constraints.	Provides high degree of freedom, Random Selection give more easy handling of structure.	Random Data Structure.
14	Kleinbort M. et al., **2019**	Rapidly Exploring Random Tree Algorithm (RRT)-Designed to solve non homonymic constraints.	Provides high degree of freedom, Random Selection give more easy handling of structure.	Random Data Structure.
15	Yuan C. et al., **2020**	Rapidly Exploring Random Tree Algorithm (RRT)-Designed to solve non homonymic constraints.	Provides high degree of freedom, Random Selection give more easy handling of structure.	Random Data Structure.
16	Pharpatara P. et al., **2017**	RRT*(Rapidly-exploring Random Trees)[5]	Probabilistic delay of failure is almost zero, Less costly, More accurate result	Its main focus was on electronics research, Structure is dynamic
17	Yuncheng Li. et al., **2017**	RRT*(Rapidly-exploring Random Trees)[5]	Probabilistic delay of failure is almost zero, Less costly, More accurate result	Its main focus was on electronics research, Structure is dynamic
18	Ichnowski J. et al., **2018**	Parallel RTT*	Multirobot planner, Scalable, y exhibit super linear speedup	Multicore CPUs, Not suitable for static environment
19	R. Cui R. et al., **2018**	Multidimensional RTT*	High efficiency and cost effectiveness	Less effective under unknown environment
20	Guo M. et al., **2018**	Probabilistic Motion Planning Algorithm(PMPA)-Provides an extension of RRTA provides an collision	Random selection give ease to understand algorithm, Accurate result.	Complexity is increases as the random selection of node is done.

		free path prediction.		
21	Chiang H. et al., **2019**	RL-RTT*	Effective to find shortest path with minimum time	Need more iteration to converge
22	Luo M. et al., **2019**	Bioinspired Neural Network Algorithm	Highly scalable, effective to find optimal path, Less complex than NN.	Need Higher dimensional environment, Requires real time data processing, Response time is little high.
23	J. Yuan J. et al., **2019**	GRU-RNN Network Model	It is very simple and easy to understand, Less complexities	Distortion can change the output (prediction)
24	J. Liang J. et al., **2020**	RNN-Recurrent Neural Network	It can manage real-time physical constraints and collision avoidance.	Redesigning is not easy, Not effective for path re-planning, Static planner.
25	Ladosz P. et al., **2020**	Obstacle Trajectory Planning for Path Prediction (OBTPP)-Based on Gaussian-process model to generate clusters for path prediction.	Easy to understand and implement, Uses Clustering techniques that provides good network.	Needs more space for storing cluster data.
26	Jeong Y. et al., **2020**	Social-LSTM- It uses pedestrian current hidden states for predicting future position of target.	It has more secure framework, Experimental result is more accurate.	Needs network security, As social pedestrian is included in network hence much prone to attack.
27	Jeong Y. et al., **2020**			

Table. 1. Comparison of existing path planning techniques/methodologies.

3. Proposed Methodology

Dynamic RRT* is proposed having good convergence rate for the prediction of final path. It is also optimal in terms of generated path. The proposed planner is presented in this section that takes initial position (Xstart) and the final destination position as (XGoal) as a input and produces a Graph that make a path from source to a destination using the proposed Dynamic RRT* algorithm. The proposed planner extend the path from a give source based on the Near and a steer function that consider nearest point to travel along the path and a mininmum distance approach towards the destination. The major objective of this dynamic planner is to generate obstacle free path.

Given a path planning problem (Xfree, Xinit, Xgoal), find a feasible path G : [0, 1] → Xfree such that G(0) = Xinit and G(1) = near(Xgoal), if one exists else report failure.

Dynamic RRT* algorithm:

Input: R_{start}, R_{Goal}

Output: G(V,E)

1. $V \leftarrow \{R_{init}\}$
2. $E \leftarrow \phi$

3. $R_{rand} \leftarrow$ Samplefree(i)

4. $R_{nearest} \leftarrow$ Nearest $((V, E),\ R_{rand})$

5. $R_{new} \leftarrow$ steer $(R_{nearest},\ R_{rand})$

    a. if obstaclefree $(R_{nearest},\ R_{new})$:

6. $R_{near} \leftarrow$ Near $((V, E),\ R_{new}, r_n)$

7. $V \leftarrow V \cup \{R_{new}\}$

8. $R_{min} \leftarrow R_{nearest}$

9. $c_{min} \leftarrow$ Cost $(x_{nearest})$ + c (Line (R_{neare}

10. for each $R_{near} \in R_{near}$

11. if CollisionFree$(R_{near},\ R_{new})$

12. if Cost(R_{near}) + c (Line $(R_{near},\ R_{new})$)

13. $R_{min} \leftarrow R_{near}$

14. $c_{min} \leftarrow$ Cost(x_{near}) + c (Line $(R_{near},\ R_{new})$)

15. $E \leftarrow E \cup \{(R_{min},\ R_{new}\}$

16. for each $R_{near} \in R_{near}$

17. if CollisionFree$(R_{new},\ R_{near})$

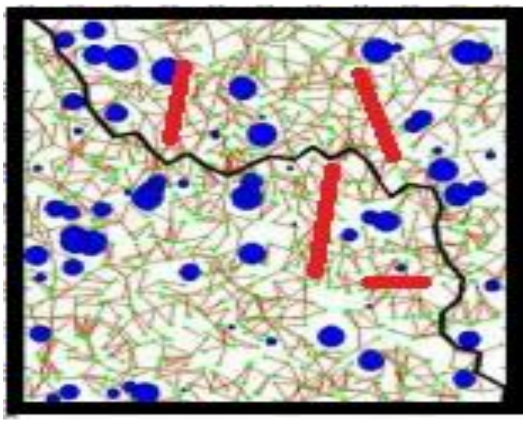
18. $t \leftarrow$ Cost(R_{new}) + c (Line $(R_{new},\ R_{near}$

19. if $t < Cost(R_{near})$

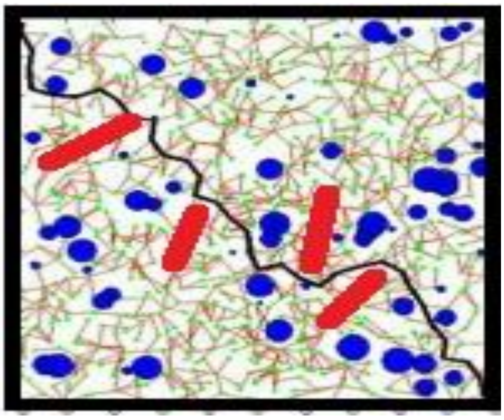
20. $R_{parent} \leftarrow$ Parent (R_{near})

21. $E \leftarrow (E \setminus \{(R_{parent},\ R_{near})\}) \cup \{(R_{new},\ R_{near}$

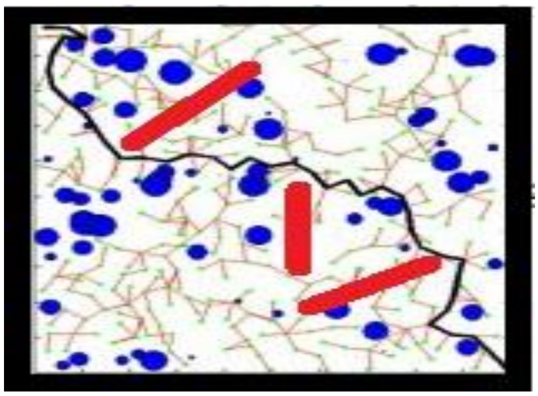
22. return (V, E)



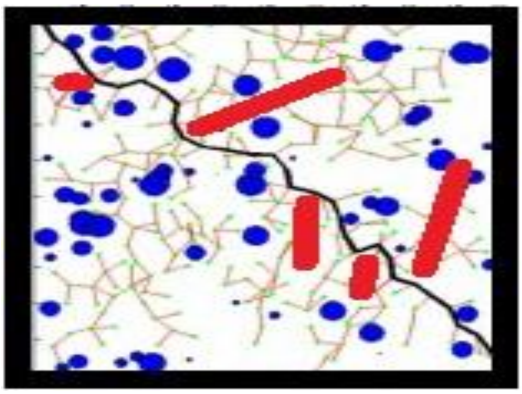
(a) Iteration-1



Iteration-2



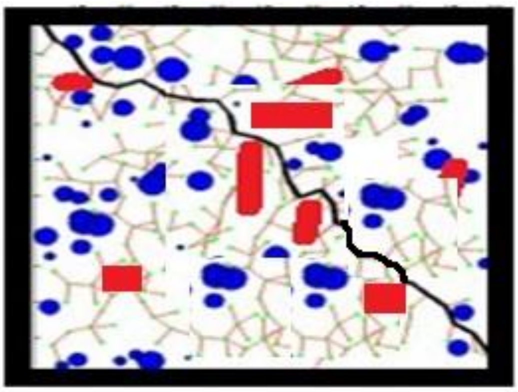
Iteration-3



Iteration-4

4. Results

The simulation results of proposed algorithm are presented in the Figure. 1, shows the convergence of Dynamic RRT* Algorithm during the iterations and the states of generated path can be observed in the results. The proposed algorithm after the convergence is also been analysed and the graphs based on path length and the navigation time over generated path is presented in this section.



Final Iteration

Fig.1 iteration-1 to final iteration during convergence of Dynamic RRT* Algorithm

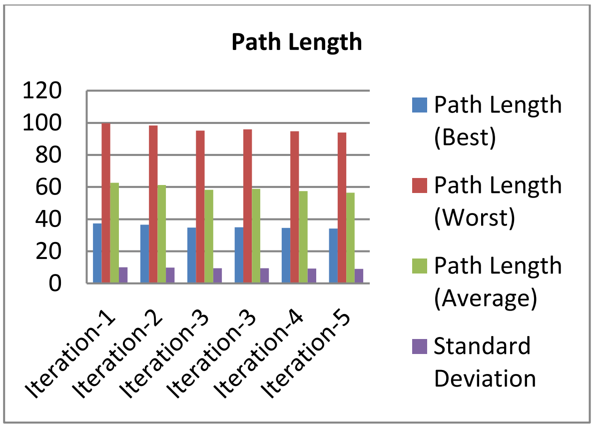


Fig.2. The length of the path without a collision as determined by simulation

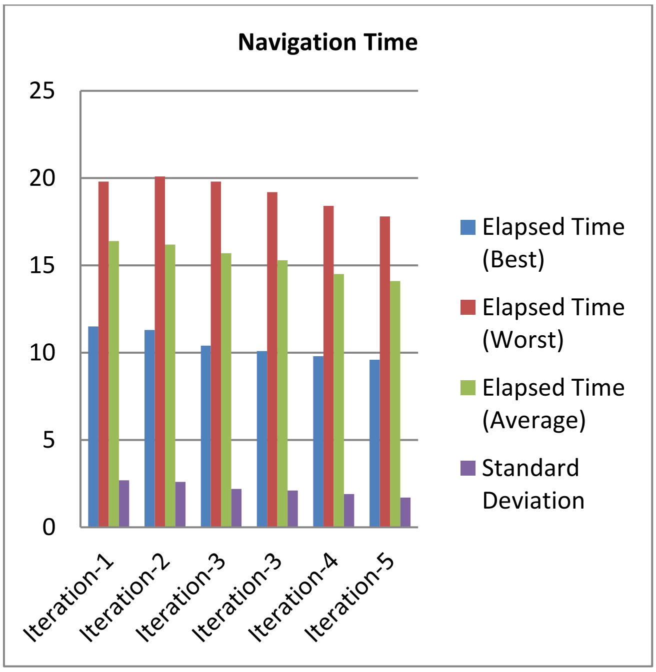


Fig. 3. Navigation Time Simulation Results with No Collisions

Figure 4 to 6, shows the simulation results obtained after the implementation of RRT*, P-RRT*, M-RRT* and Dynamic RRT* algorithm. The simulation results are also analysed base on error in the path prediction and number of collision found during navigation of the various approaches with respect to the proposed approach. The analysis and results obtained shows that the dynamic RRT* algorithm works better than some of the approaches but it shows some laggings in the path generation and the slight error is been reported in the proposed approach. However the approach can be work better if we apply some local as well as global optimization to the proposed approach.

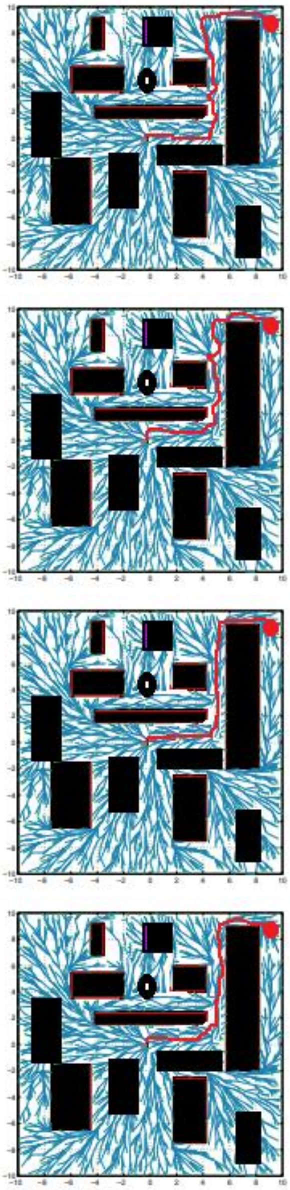
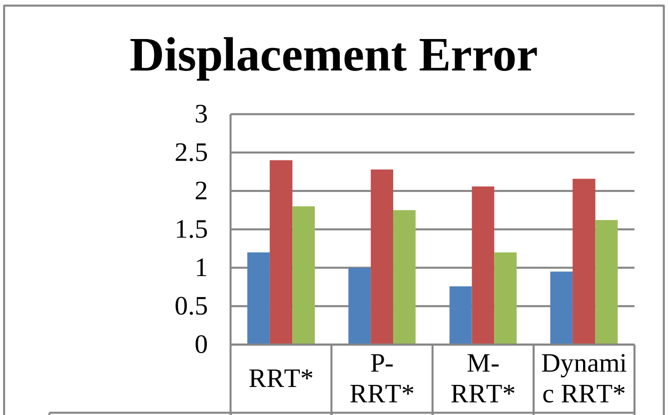
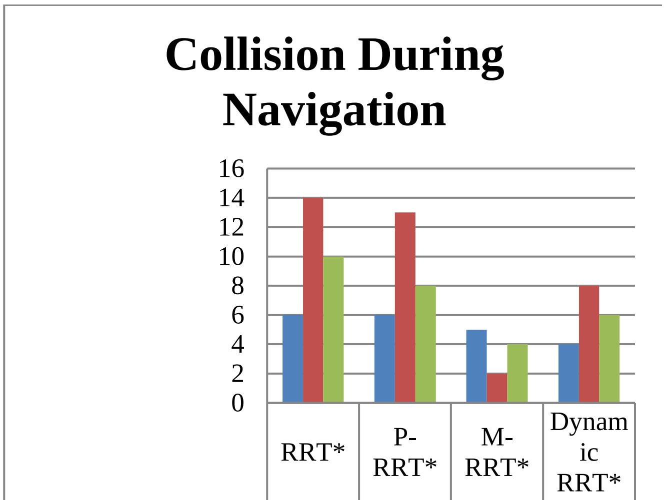


Fig.4. Path generated by the RRT*, P-RRT*, M-RRT* and Dynamic RRT*



	RRT*	P-RRT*	M-RRT*	Dynamic RRT*
Min Displacement Error	1.2	1	0.76	0.95
Max Displacement Error	2.4	2.28	2.06	2.16
Average Displacement Error	1.8	1.75	1.2	1.62

Fig. 5. Displacement Error comparison of Proposed system with existing methods.



	RRT*	P-RRT*	M-RRT*	Dynamic RRT*
No. of Collisions (Best)	6	6	5	4
No. of Collisions (Worst)	14	13	2	8
No. of Collisions (Average)	10	8	4	6

Fig. 6. Displacement Error comparison of Proposed system with existing methods.

5. Conclusion.

The paper presented the idea of dynamic path planner approaches that are used in the recent years for the motion planning of mobile robot. The sampling based approach, Rapidly exploring Random Tree (RRT) is one of the popular path planning approach has been discussed and it has been considered as base to the proposed dynamic RRT* algorithm which is presented and systematically described in one of the section of this work. The simulation results are also been presented in this work and the analysis has done in terms of predicted path length, number of nodes in the path, time to navigate over a predicted path and the displacement error in the path prediction . The result analysis shows that the proposed dynamic RRT* approach for path planning in the dynamic environment can work better if we apply some optimization at local as well as global parameter settings to the approach that that makes proposed planner robust and works more efficiently.

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