



RRT*-Quick

A Motion Planning Algorithm with Faster Convergence Rate



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Introduction

Conventional graph-based planning methods require us to **discretize** the search space.

However, as the dimension of the search space increases, the **memory requirement** grows exponentially and the solution becomes more difficult to reach.

Sampling-based algorithms are employed extensively in a **high dimensional space** and are shown to work well. Besides they are also theoretically proven to be **probabilistically complete and asymptotically optimal**.

In this project, we explore **RRT*-Quick** as an improved version of RRT*

RRT

- searches for a ***feasible*** trajectory
- repeatedly connect a randomly sampled state to nearest node in the existing tree if there is no collision
- **no improvement** with increase in iterations, as there is no rewiring or tracking of cost

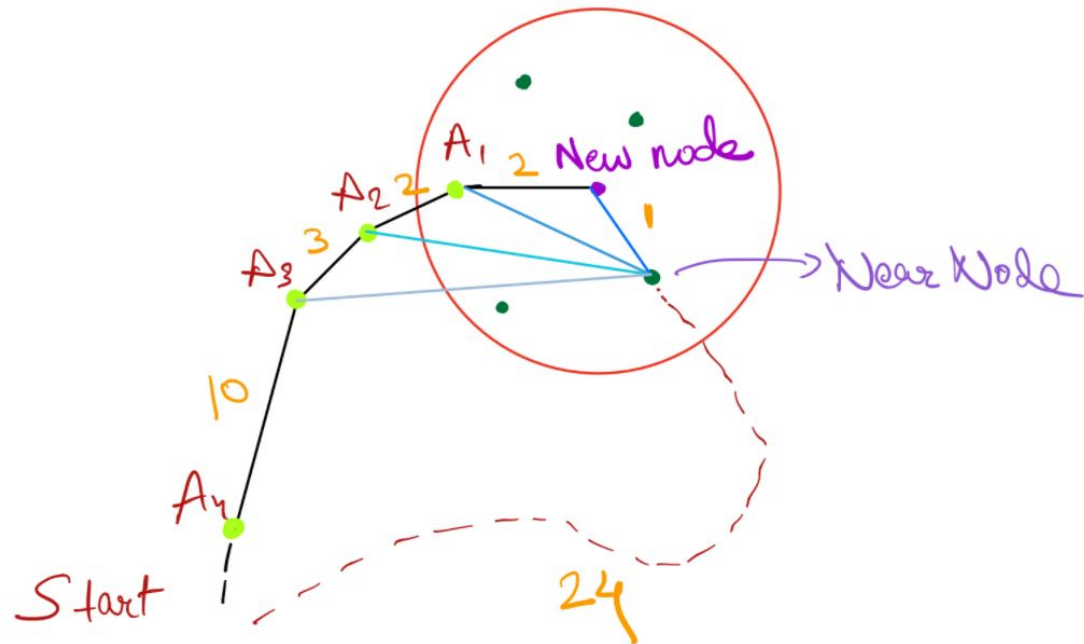
RRT*

- focuses on *improving* the quality of solutions
- While RRT simply connects a random sample to the nearest node, RRT* searches the nearby nodes within a **volume sphere** to find that node which makes the lowest cost-to-come to the new node
- It also tries to **rewire the nearby nodes via the new node** if it lowers their cost
- converges to optimal as iterations increase, **radius** of the volume sphere decides the converge rate

RRT* Quick

- The concept of RRT* Quick is based on the premise that nearby nodes tend to share ***common parents***
- **Triangular inequality:**
If we rewire the nearby nodes **via parents** of the new node **instead of the new node itself**, it will definitely result in lower cost

RRT* Quick



Pseudocode

Input: $T = (V, E)$

Output: T

while $i < N$ do

$x_{rand} \leftarrow \text{Sample}(i)$;

$x_{nearest} \leftarrow \text{Nearest}(T, x_{rand})$;

$x_{new} \leftarrow \text{Extend}(x_{nearest}, x_{rand})$;

$\sigma_{new} \leftarrow \text{Steer}(x_{nearest}, x_{rand})$;

if $\text{CollisionFree}(\sigma_{new})$ **then**

$X_{near} \leftarrow \text{Near}(T, x_{new})$;

$x_{min} \leftarrow x_{nearest}$;

$c_{min} \leftarrow \text{Cost}(x_{nearest}) + \text{Cost}(\sigma_{new})$;

foreach $x_{near} \in X_{near}$ **do**

$\sigma_{near} \leftarrow \text{Steer}(x_{near}, x_{new})$;

if $\text{Cost}(x_{near}) + \text{Cost}(\sigma_{near}) < c_{min} \wedge \text{CollisionFree}(\sigma_{near})$ **then**

$x_{min} \leftarrow x_{near}$;

$c_{min} \leftarrow \text{Cost}(x_{near}) + \text{Cost}(\sigma_{near})$;

end

end

$V \leftarrow V \cup x_{new}$;

$E \leftarrow E \cup \{(x_{min}, x_{new})\}$;

foreach $x_{near} \in X_{near}$ **do**

$\sigma_{near} \leftarrow \text{Steer}(x_{new}, x_{near})$;

if $\text{Cost}(x_{new}) + \text{Cost}(\sigma_{near}) < \text{Cost}(x_{near}) \wedge \text{CollisionFree}(\sigma_{near})$

then

$E \leftarrow E \setminus \{(\text{Parent}(x_{near}), x_{near})\}$;

$E \leftarrow E \cup \{(x_{new}, x_{near})\}$;

end

end

end

end

$T \leftarrow (V, E)$;

return T ;

RRT*

Input: $T = (V, E)$

Output: T

while $i < N$ do

$x_{rand} \leftarrow \text{Sample}(i)$;

$x_{nearest} \leftarrow \text{Nearest}(T, x_{rand})$;

$x_{new} \leftarrow \text{Extend}(x_{nearest}, x_{rand})$;

$\sigma_{new} \leftarrow \text{Steer}(x_{nearest}, x_{rand})$;

if $\text{CollisionFree}(\sigma_{new})$ **then**

$X_{near} \leftarrow \text{Near}(T, x_{new})$;

$x_{min} \leftarrow x_{nearest}$;

$c_{min} \leftarrow \text{Cost}(x_{nearest}) + \text{Cost}(\sigma_{new})$;

foreach $x_{near} \in X_{near} \cup \text{Ancestors}(X_{near}, \text{degree})$ **do**

$\sigma_{near} \leftarrow \text{Steer}(x_{near}, x_{new})$;

if $\text{Cost}(x_{near}) + \text{Cost}(\sigma_{near}) < c_{min} \wedge \text{CollisionFree}(\sigma_{near})$ **then**

$x_{min} \leftarrow x_{near}$;

$c_{min} \leftarrow \text{Cost}(x_{near}) + \text{Cost}(\sigma_{near})$;

end

end

$V \leftarrow V \cup x_{new}$;

$E \leftarrow E \cup \{(x_{min}, x_{new})\}$;

foreach $x_{near} \in X_{near}$ **do**

$\sigma_{near} \leftarrow \text{Steer}(x_{new}, x_{near})$;

$X_{candidates} \leftarrow \text{Ancestors}(x_{new}, \text{degree}) \setminus \text{Ancestors}(x_{near}, \text{degree})$;

$x_{min} \leftarrow x_{new}$;

$c_{min} \leftarrow \text{Cost}(x_{new}) + \text{Cost}(\sigma_{new})$;

foreach $x_c \in X_{candidates}$ **do**

$\sigma_c \leftarrow \text{Steer}(x_c, x_{near})$;

if $\text{Cost}(x_c) + \text{Cost}(\sigma_c) < c_{min} \wedge \text{CollisionFree}(\sigma_c)$ **then**

$x_{min} \leftarrow x_c$;

$c_{min} \leftarrow \text{Cost}(x_c) + \text{Cost}(\sigma_c)$;

end

end

$E \leftarrow E \setminus \{(\text{Parent}(x_{near}), x_{near})\}$;

$E \leftarrow E \cup \{(x_{min}, x_{near})\}$;

end

end

end

$T \leftarrow (V, E)$;

return T ;

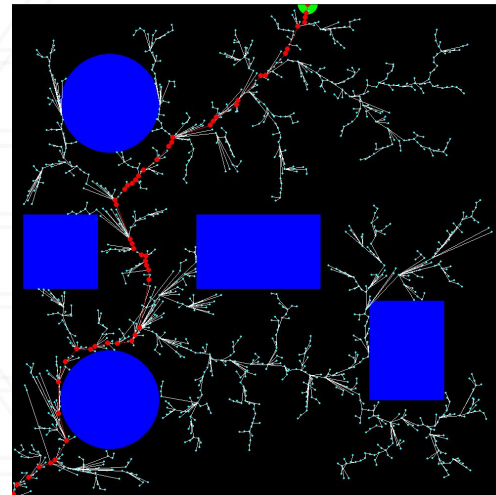
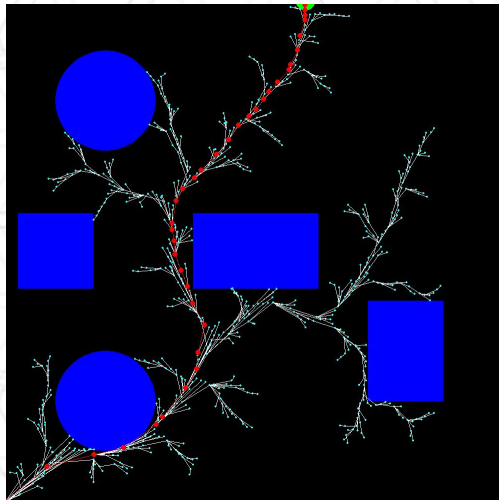
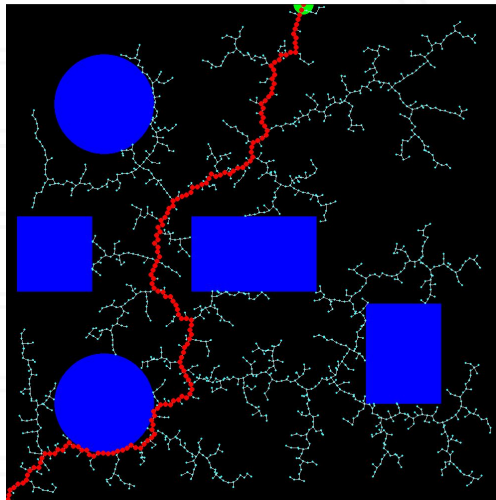
RRT* Quick

Increasing Radius vs Using Ancestors ?

ROS Gazebo Simulation Turtlebot(WIP)

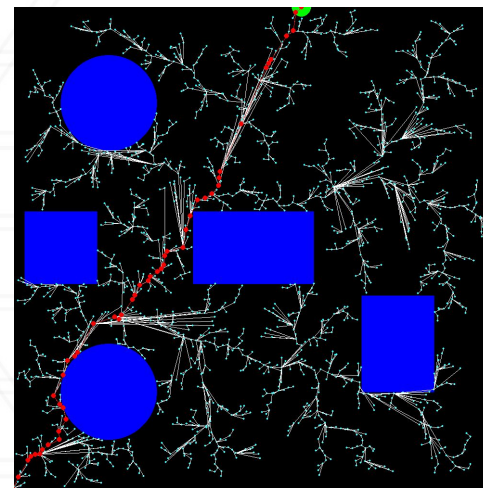
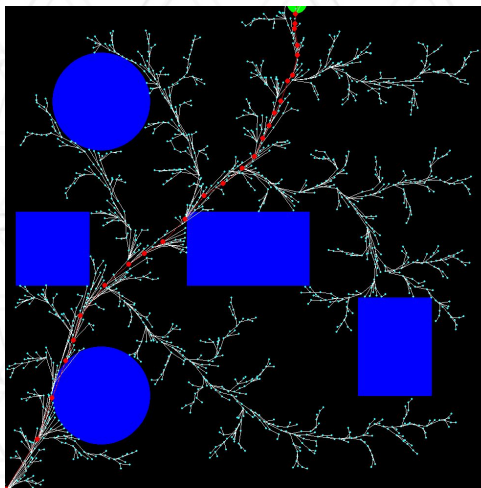
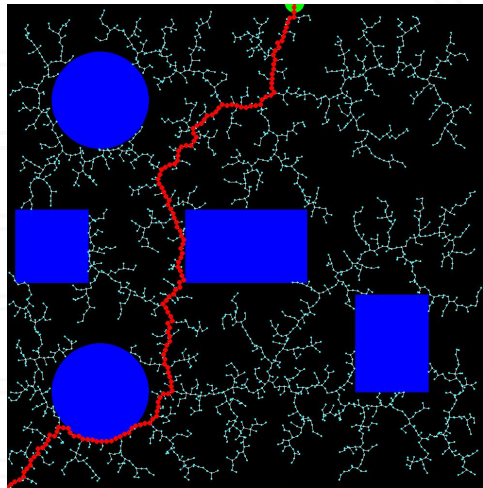
- 2 nodes (RRT* Quick → Robotcontrol)
- Movebase Action client(Robot control)
- AMCL (Adaptive Monte Carlo Localization)
- Waypoint coordinates transmitted to the main controller node by RRT node.

RRT vs RRT* vs RRT* Quick



2000 iterations

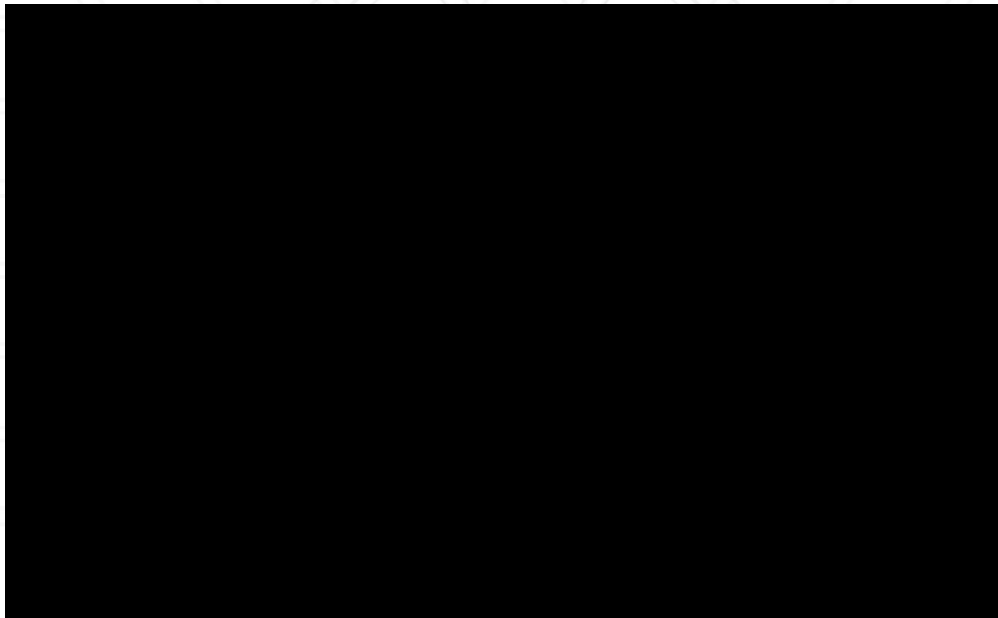
RRT vs RRT* vs RRT* Quick



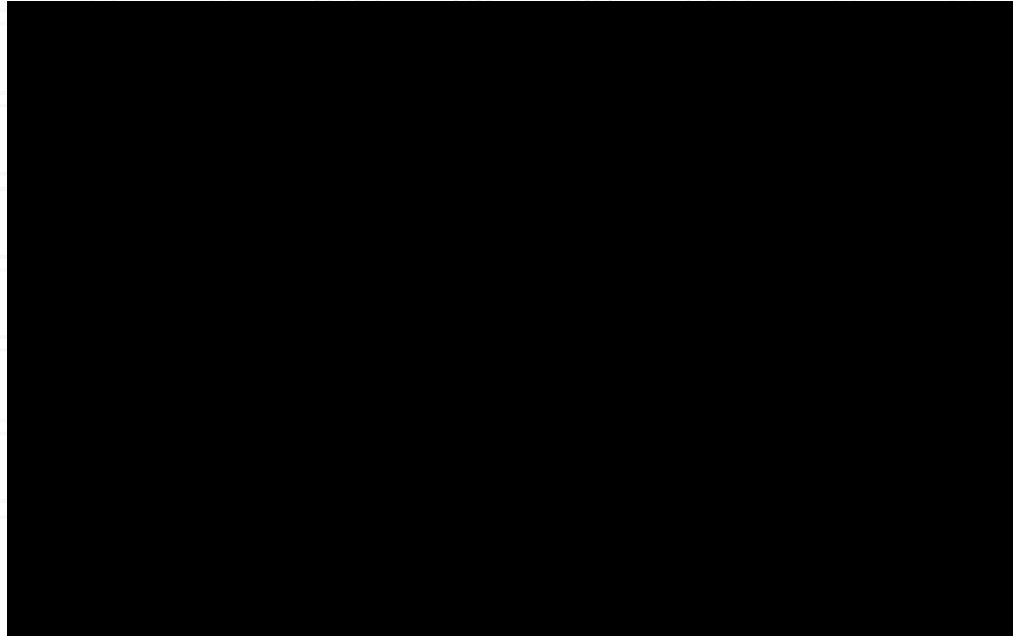
3000 iterations

Visualization

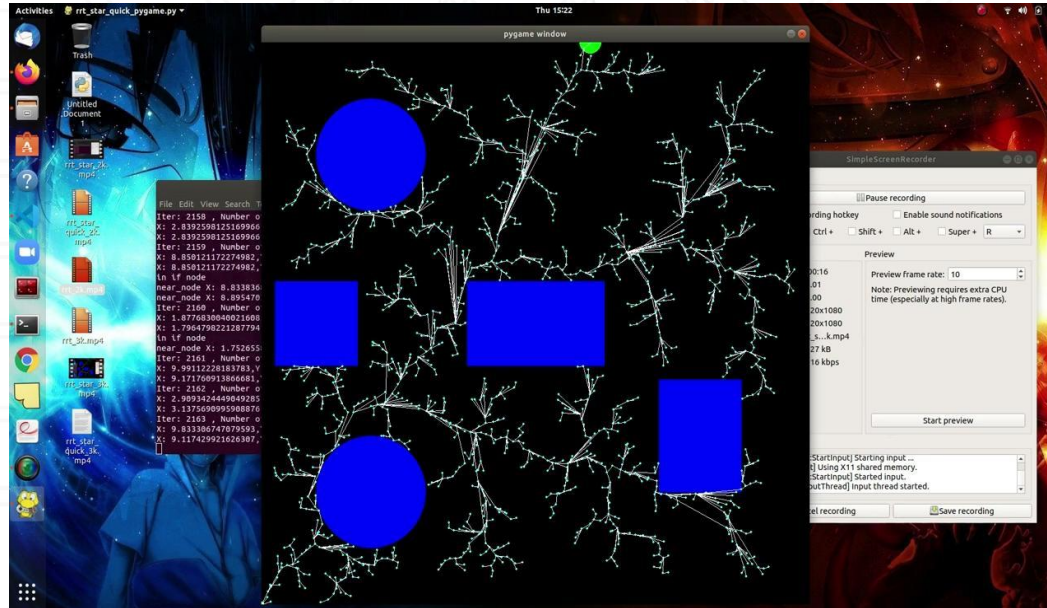
RRT(3000 iterations)



RRT*(3000 iterations)



RRT* Quick(3000 iterations)



Conclusion and Future Work

- RRT* Quick performs much better than RRT and RRT* with almost same time complexity
 - Implement Cost to go with RRT* Quick to even improve it further.
 - Multi-agent path planning using RRT* Quick.



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