

Path Planning Probabilistico

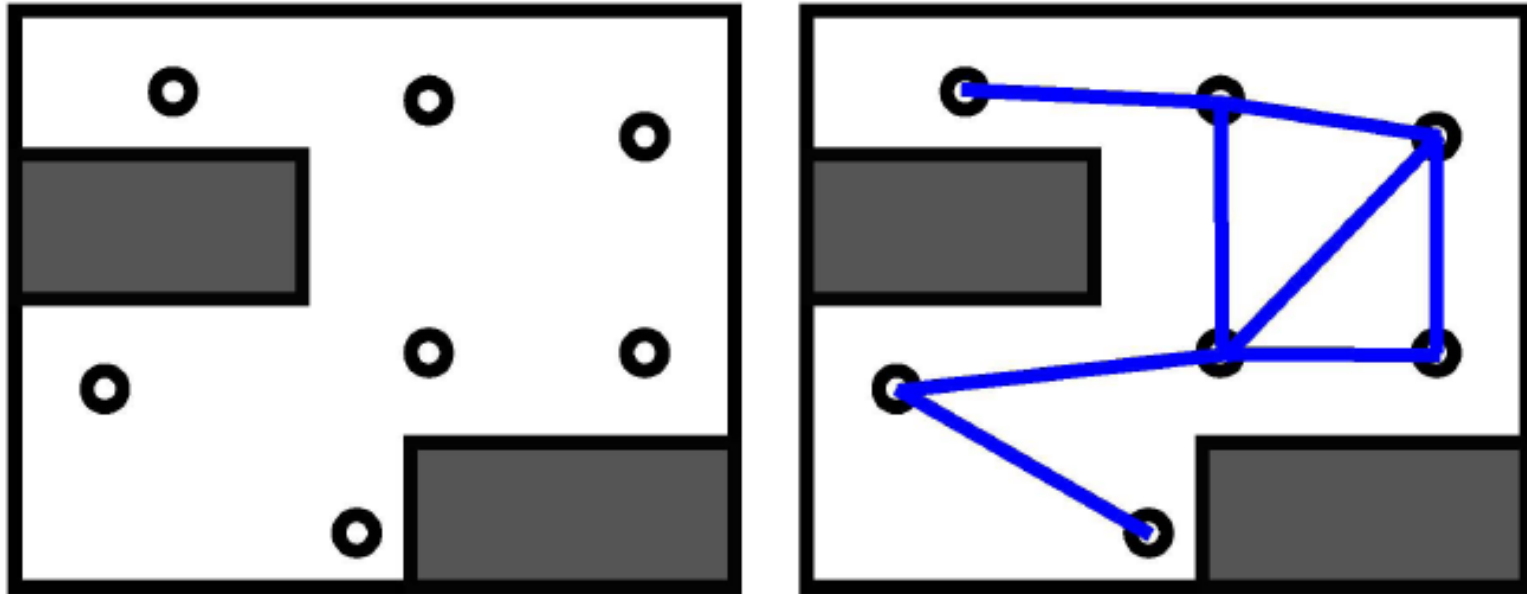
- Continuous state spaces
- Continuous actions
- PRM (Kavraki & many successors)
- RRT (Lavalle & many successors)

Probabilistic Roadmap

- Separate planning into two stages
 - “Learning” Phase
 - random samples of free configurations (vertices)
 - Attempt to connect pairs of nearby vertices with a local planner
 - if a valid plan is found, add an edge to the graph
 - Query Phase
 - find local connections to graph from initial and goal positions

Fase di Learning

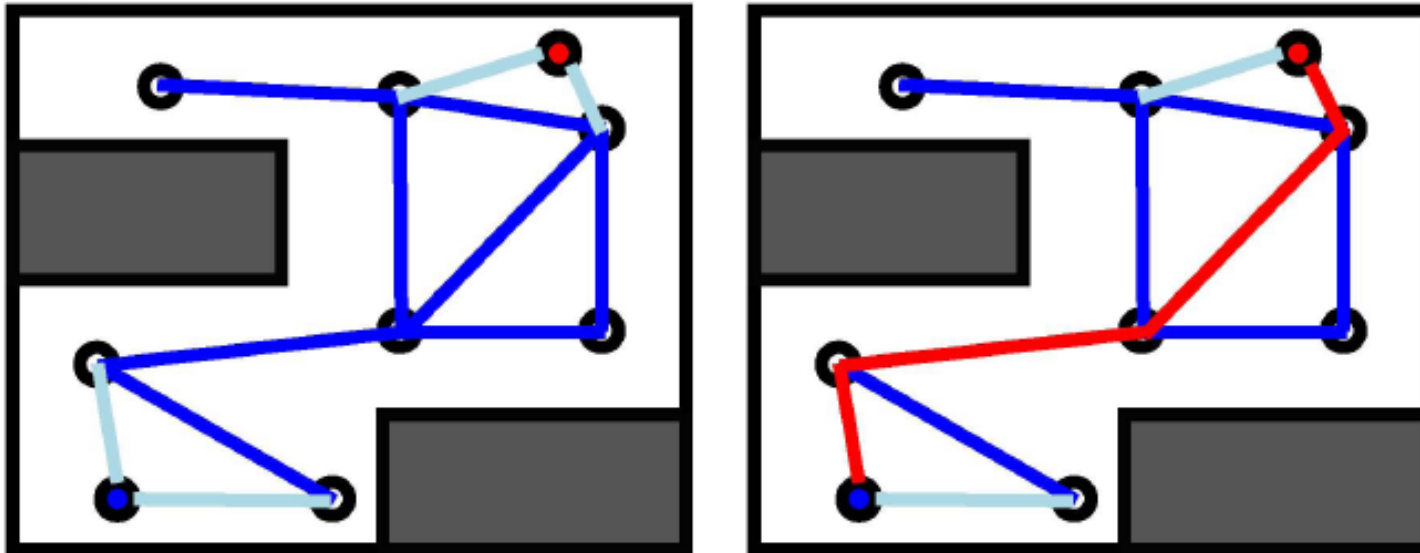
Learning Phase:



Configurazione random nello spazio libero, poi connessa da archi collegando tutti i k vicini a distanza minore di n

Fase di Query

Query Phase:



Nella fase di Query si connette goal e posizione iniziale e si cerca lo shortest path (A*, Dijkstra)

E' probabilisticamente completo: all'aumentare dei punti, la probabilità di non trovare il percorso va a zero

Rapidly Exploring Random Trees

- RRT
 - Explore continuous spaces efficiently
 - No need for an artificial grid
 - Form the basis for probabilistically complete planner
- Complete planners exist, but are slow
- RRT uses random search and approximation for speed

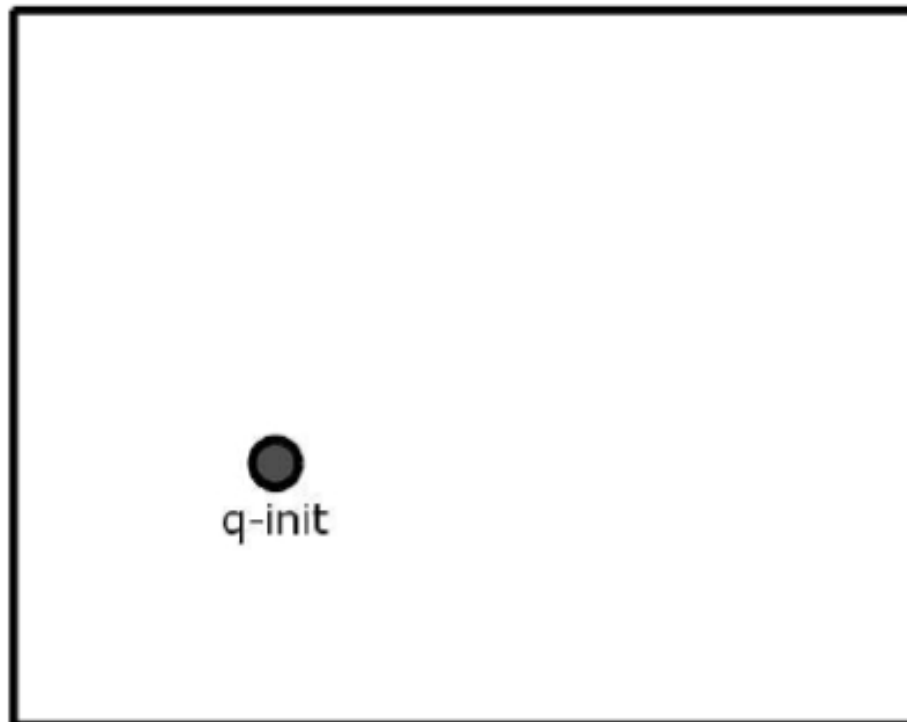
RRT: Algoritmo

Basic RRT Algorithm:

- (1) Initially, start with the initial configuration as root of tree
- (2) Pick a random state in the configuration space
- (3) Find the closest node in the tree
- (4) Extend that node toward the state if possible
- (5) Goto (2)

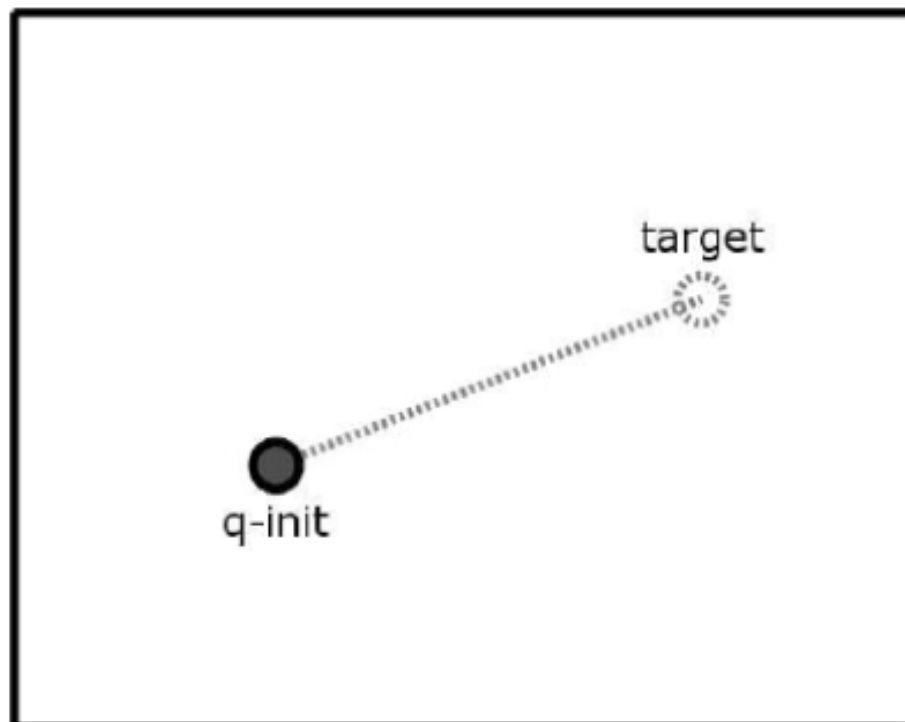
RRT: Esempio (inizio)

(1) Start with the initial state as the root of a tree



RRT: Esempio (Esplorazione)

- (2) Pick a random state in the environment
- (3) Find the closest node in the tree

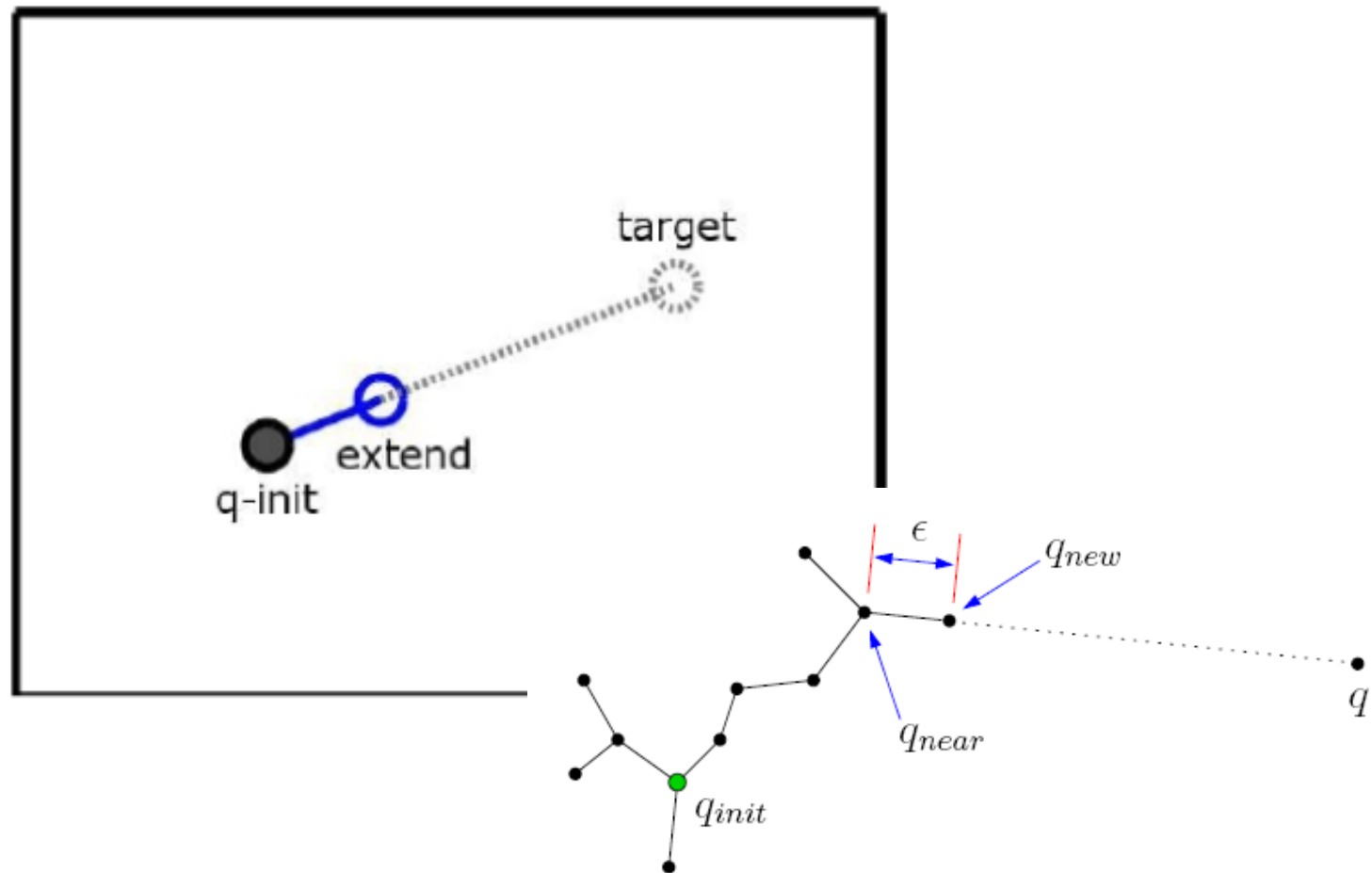


Simmons, Veloso,

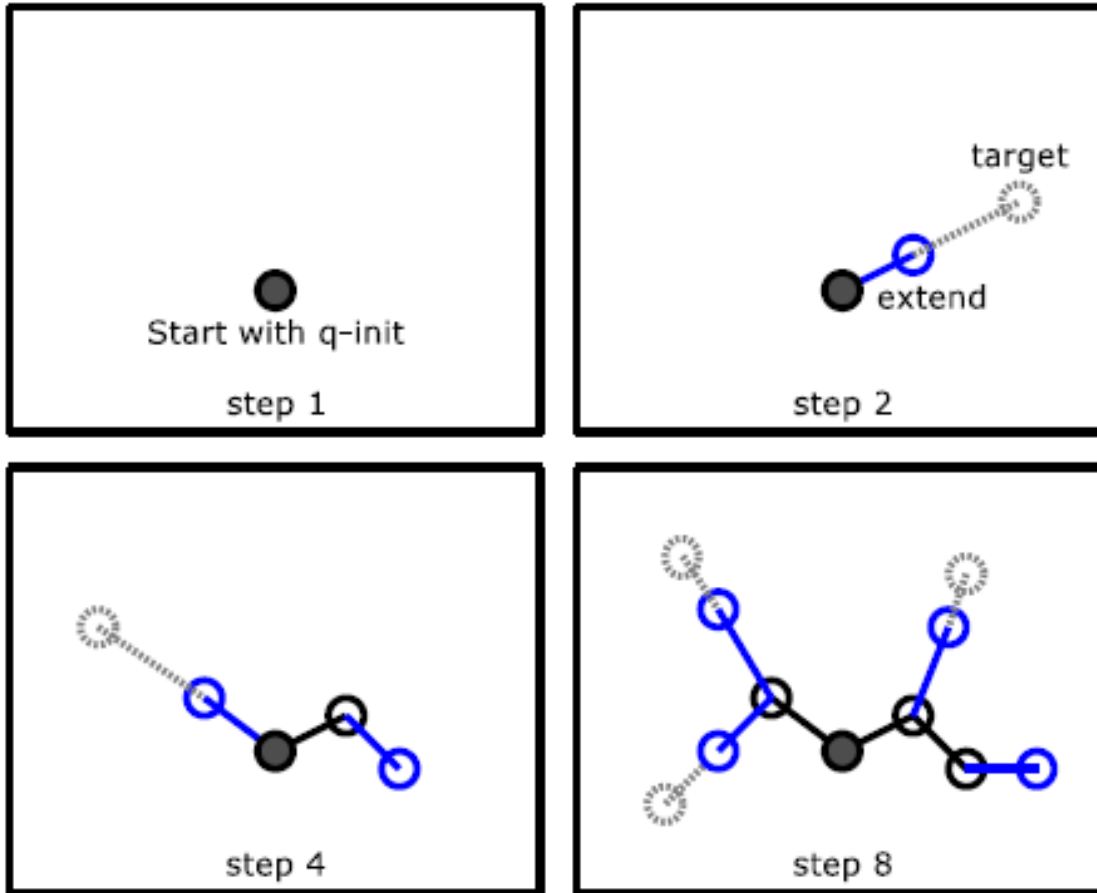
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Fall 2008

RRT: Esempio (Ricerca)

(4) Extend that node toward the target



RRT: Esempio (Ricerca)



RRT: Algoritmo

Algorithm BuildRRT

Input: Initial configuration q_{init} , number of vertices in RRT K , incremental distance Δq

Output: RRT graph G

$G.init(q_{init})$

for $k = 1$ **to** K

$q_{rand} \leftarrow \text{RAND_CONF}()$

$q_{near} \leftarrow \text{NEAREST_VERTEX}(q_{rand}, G)$

$q_{new} \leftarrow \text{NEW_CONF}(q_{near}, \Delta q)$

$G.add_vertex(q_{new})$

$G.add_edge(q_{near}, q_{new})$

return G

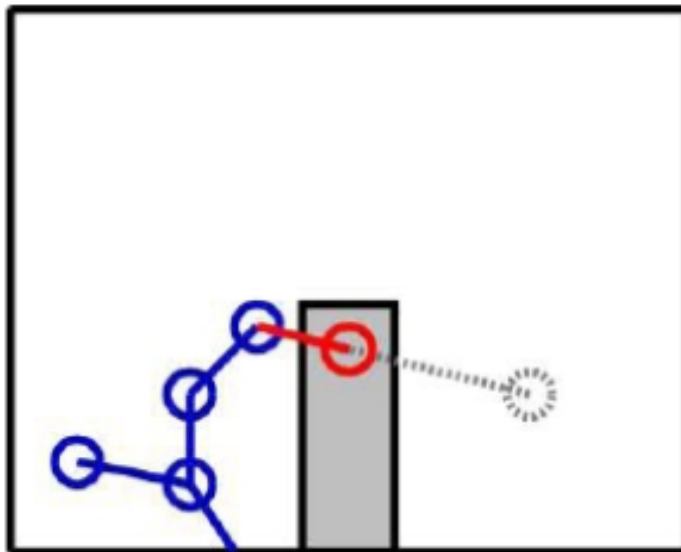
Algorithm 3: RRT.

```
1  $V \leftarrow \{x_{init}\}; E \leftarrow \emptyset;$ 
2 for  $i = 1, \dots, n$  do
3    $x_{rand} \leftarrow \text{SampleFree}_i;$ 
4    $x_{nearest} \leftarrow \text{Nearest}(G = (V, E), x_{rand});$ 
5    $x_{new} \leftarrow \text{Steer}(x_{nearest}, x_{rand});$ 
6   if  $\text{ObstacleFree}(x_{nearest}, x_{new})$  then
7      $V \leftarrow V \cup \{x_{new}\}; E \leftarrow E \cup \{(x_{nearest}, x_{new})\};$ 
8 return  $G = (V, E);$ 
```

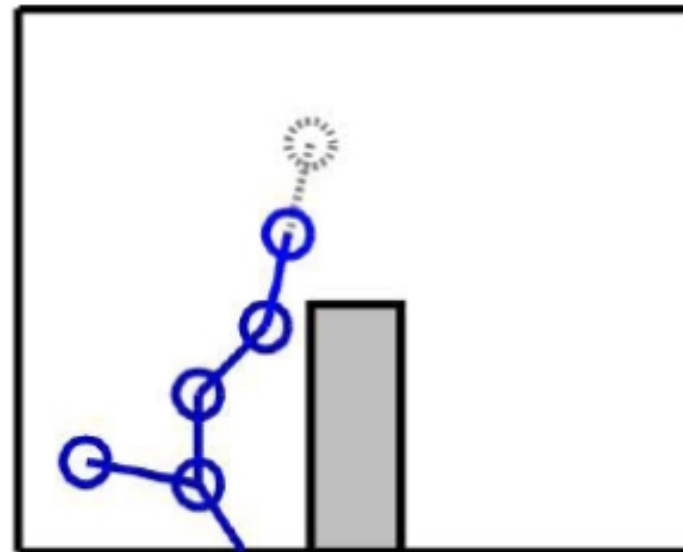


RRT: Ostacoli

- Ignore extensions which hit obstacles
- Resulting tree contains *only* valid paths



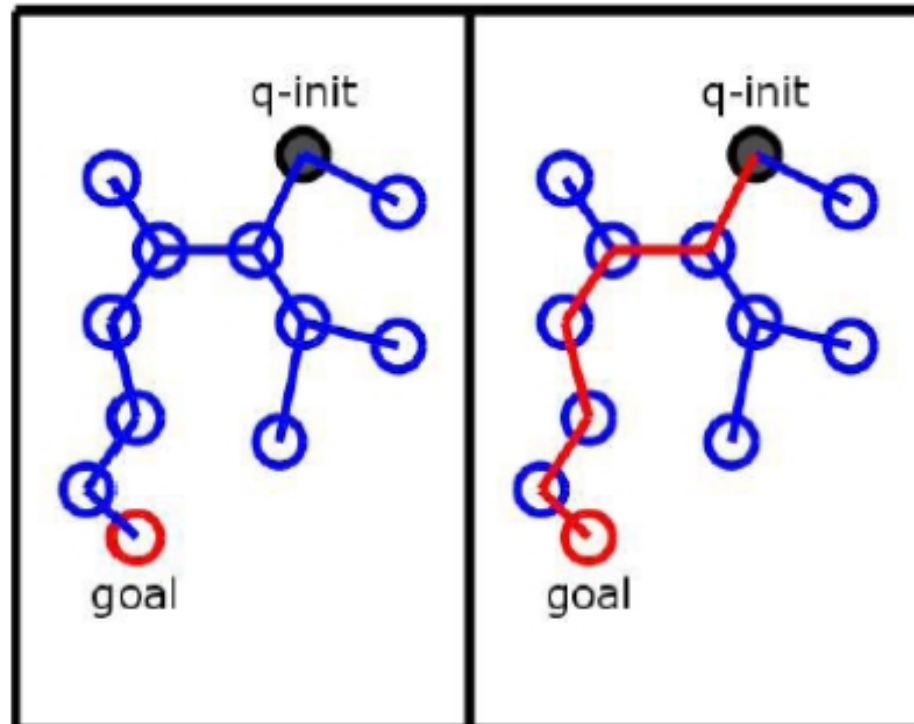
Ignore invalid extension



Record valid extension

RRT per Planning

- Once a node of the tree is a *goal*, the plan is the path back up the tree



RRT Orientato al Gol

- 1) Start with initial state as root of tree
- 2) Pick a random target state
 - o Goal configuration with probability p
 - o Random configuration with probability $1-p$
- 3) Find the closest node in the tree
- 4) Extend the closest node toward the target
- 5) Goto step 2

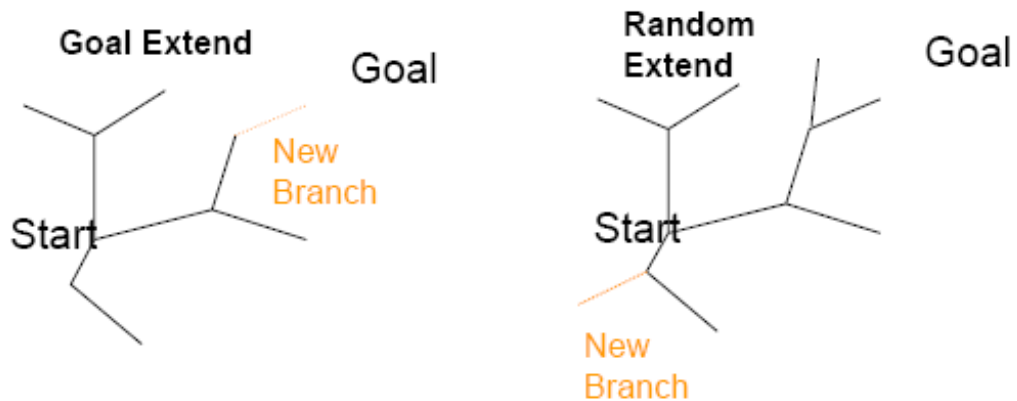
RRT Orientato al Gol

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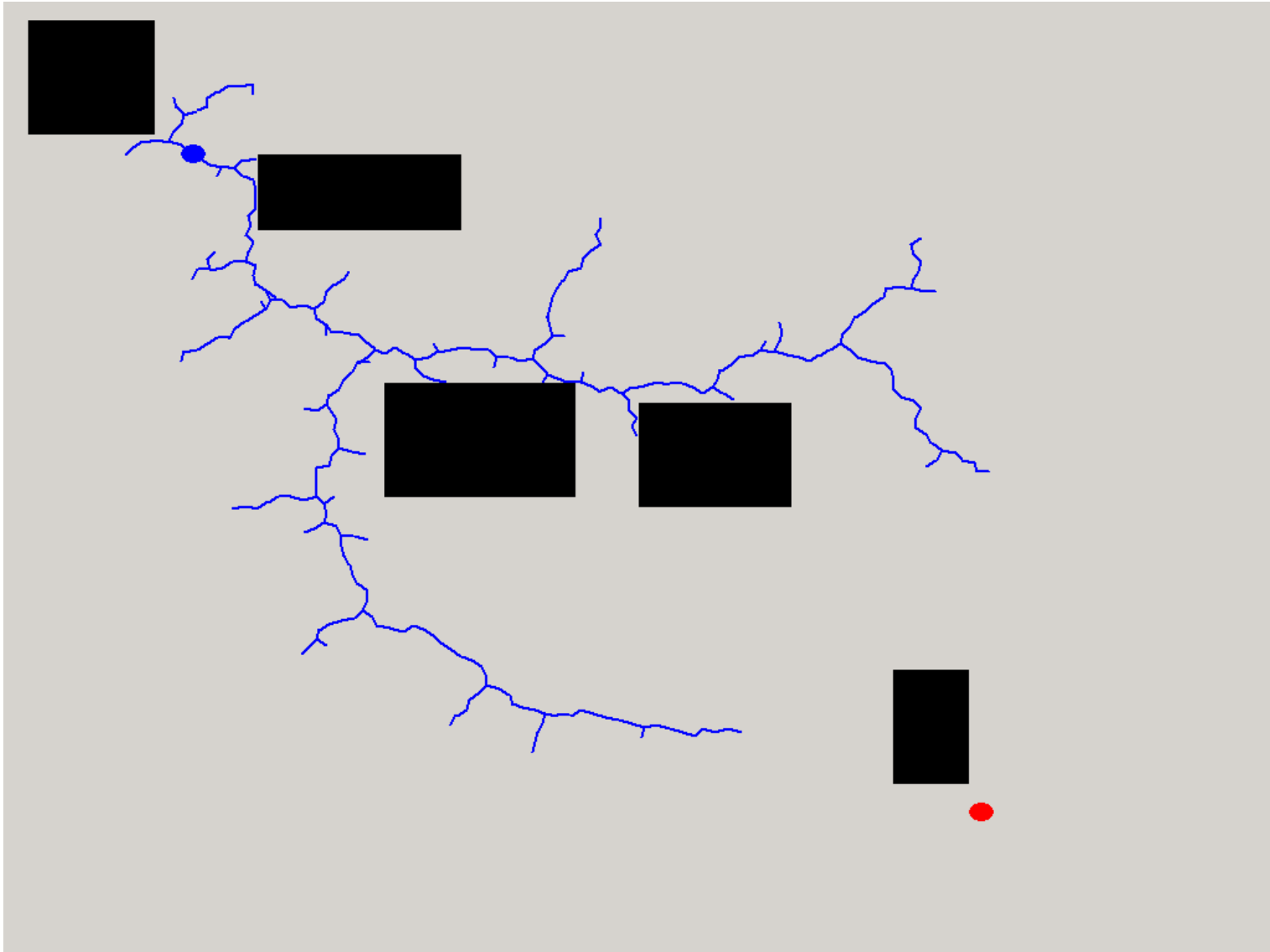
RRT per Planning

Probability p : Extend *closest node* in tree towards goal

Probability $1-p$: Extend closest node towards a random point



RRT



RRT: Algoritmo

```
function RRTPlan (env:environment,initial:state,  
                  goal:state):rrt-tree  
  var nearest,extended,target:state;  
  var tree:rrt-tree;  
  nearest := initial;  
  rrt-tree := initial;  
  while(Distance (nearest,goal) < threshold)  
    target = ChooseTarget (goal);  
    nearest = Nearest (tree,target);  
    extended = Extend (env,nearest,target);  
    if extended  $\neq$  EmptyState then  
      AddNode (tree,extended);  
  return tree;  
  
function ChooseTarget (goal:state):state  
  var p:real;  
  p = UniformRandom in [0.0 .. 1.0];  
  if 0 < p < GoalProb then  
    return goal;  
  else if GoalProb < p < 1 then  
    return RandomState();  
  
function Nearest (tree:rrt-tree,target:state):state  
  var nearest:state;  
  nearest := EmptyState;  
  foreach state s in current-tree  
    if Distance (s,target) <  
      Distance (nearest,target) then  
      nearest := s;  
  return nearest;
```

RRT: Planning/Replanning

- Environments and planning
 - Value of p ?
- Dynamic environments
- When failure, what to do?

RRT: Planning/Replanning

Plain RRT planner has little bias toward plan quality, and replanning is naive (all previous information is thrown out before replanning).

Waypoints:

- Previously successful plans can guide new search
- Biases can be encoded by modifying the target point distribution

Waypoint Cache:

- When a plan is found, store nodes into a bin with random replacement
- During target point selection, choose a random item from waypoint cache with probability q

ERRT: Execution extended RRT

Save past path as waypoints

- 1) Start with initial state as root of tree
- 2) Pick a random target state
 - o Goal configuration with probability p
 - o **Random item from waypoint cache with probability q**
 - o Random configuration with probability $1-q-p$
- 3) Find the closest node in the tree
- 4) Extend the closest node toward the target
- 5) Goto step 2

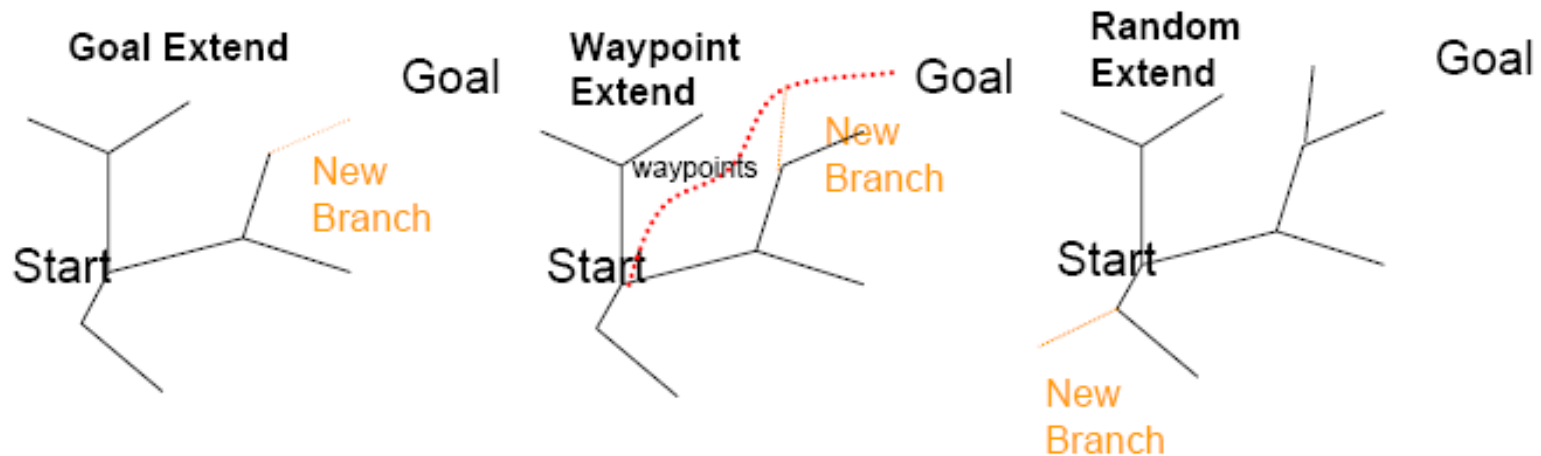
Bruce & Veloso, Real-time randomized path planning for robot navigation, 2003

ERRT: replanning

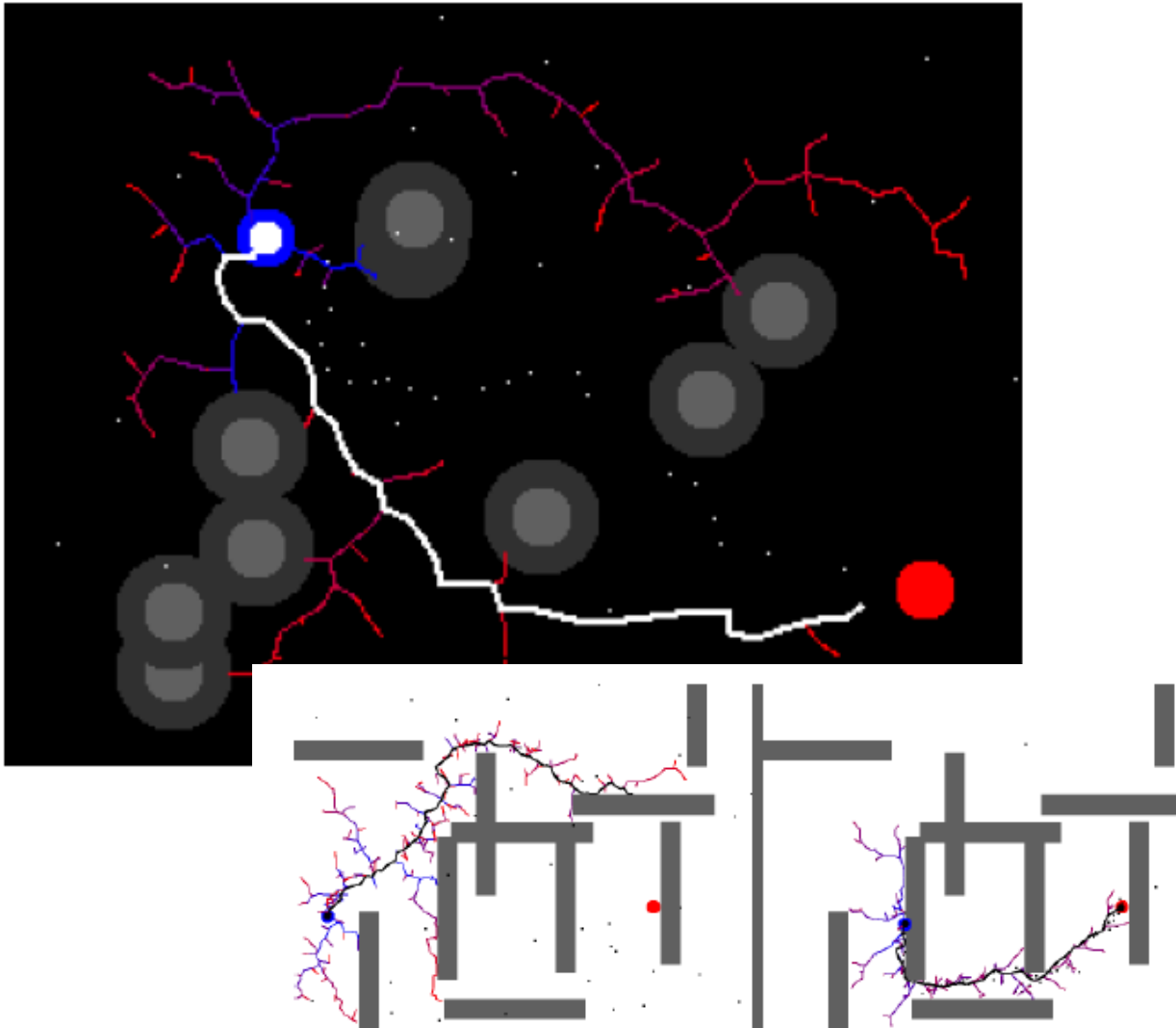
Probability p : Extend closest node in tree towards goal

Probability r : Extend closest node in tree towards random cache point

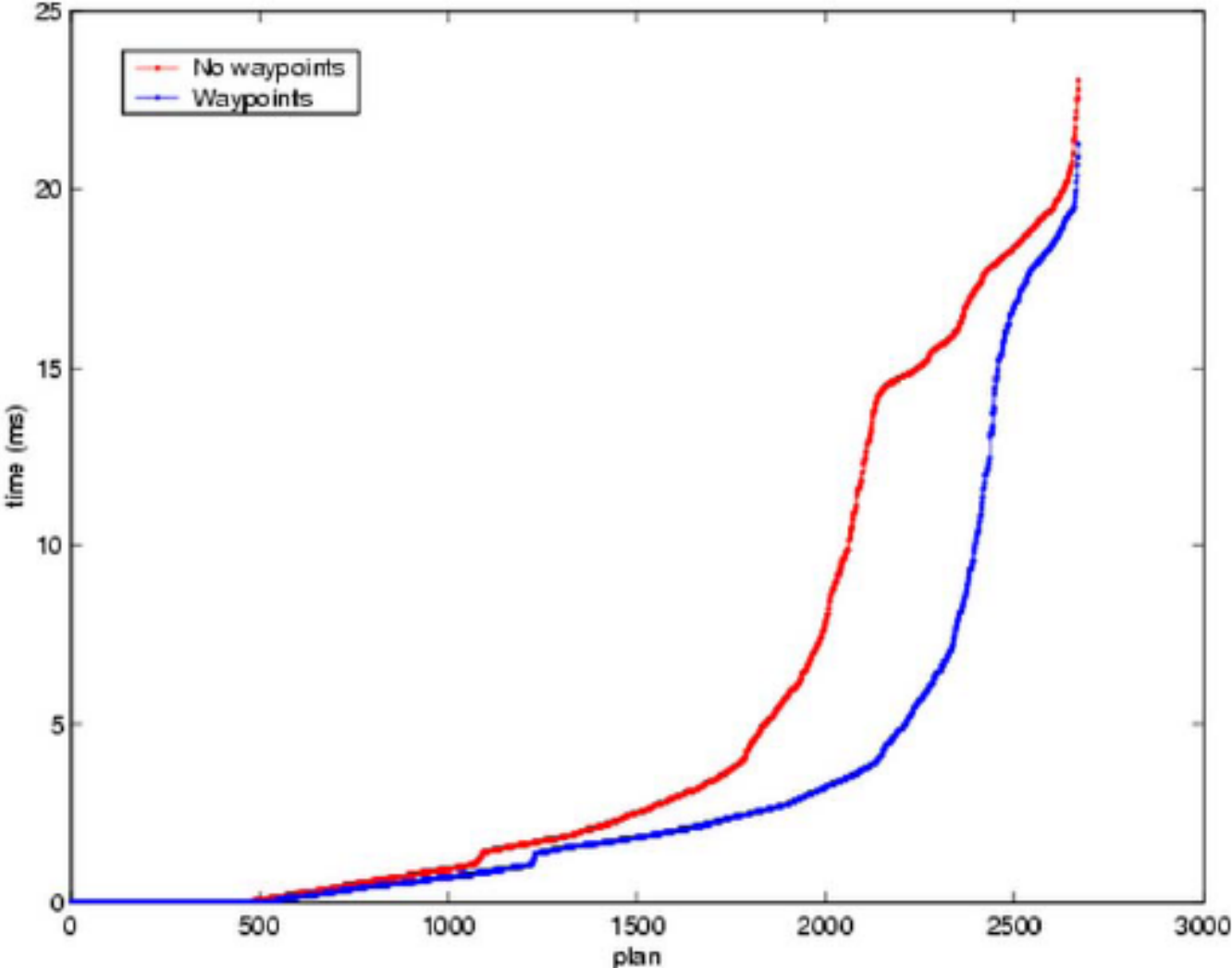
Probability $1-p-r$: Extend closest node towards a random point



ERRT: Replanning con waypoint



Prestazioni



Discussione

- Planning with RRT
 - High p – few known obstacles
 - Low p – many known obstacles
- Replanning with ERRT
 - High q – small dynamics (no state change)
 - Low q – high dynamics (lots of state change)
 - ERRT – bias to use previous plan; but could be any other bias
- RRT and ERRT – probabilistic convergence

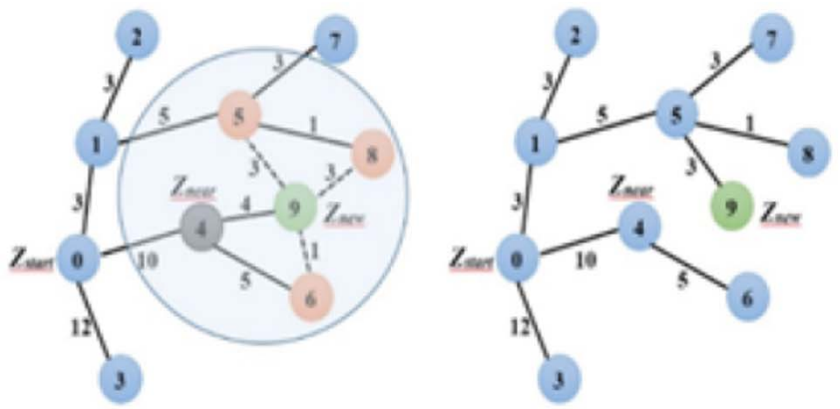
RRT*

- Ricerca dei vicini e riscrittura dell'albero
 - Ricerca:
 - miglior nodo parent per il nuovo nodo prima della sua inserzione nell'albero (nell'area di una sfera di raggio r).
 - Riscrittura:
 - rigenera l'albero nel raggio di area k per mantenere l'albero con costo minimo

S. Karaman and E. Frazzoli, "Sampling-Based Algorithms for Optimal Motion Planning," *The International Journal of Robotics Research*, 30(7), 2011 pp. 846–894.

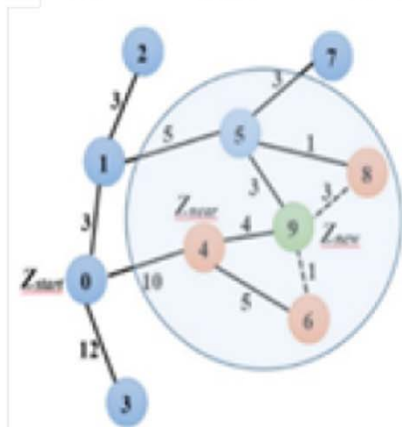
RRT*

- Ricerca dei vicini e riscrittura dell'albero

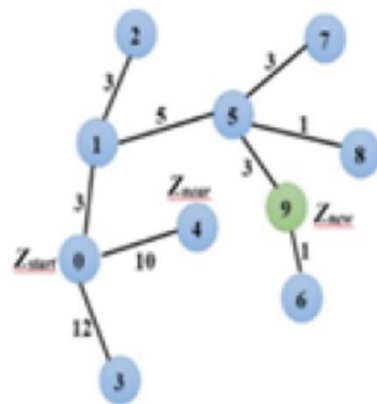


(a) Find near

(b) Select best parent.



(c) Check cost for rewiring.



(d) Rewired tree.

Algorithm 6: RRT*.

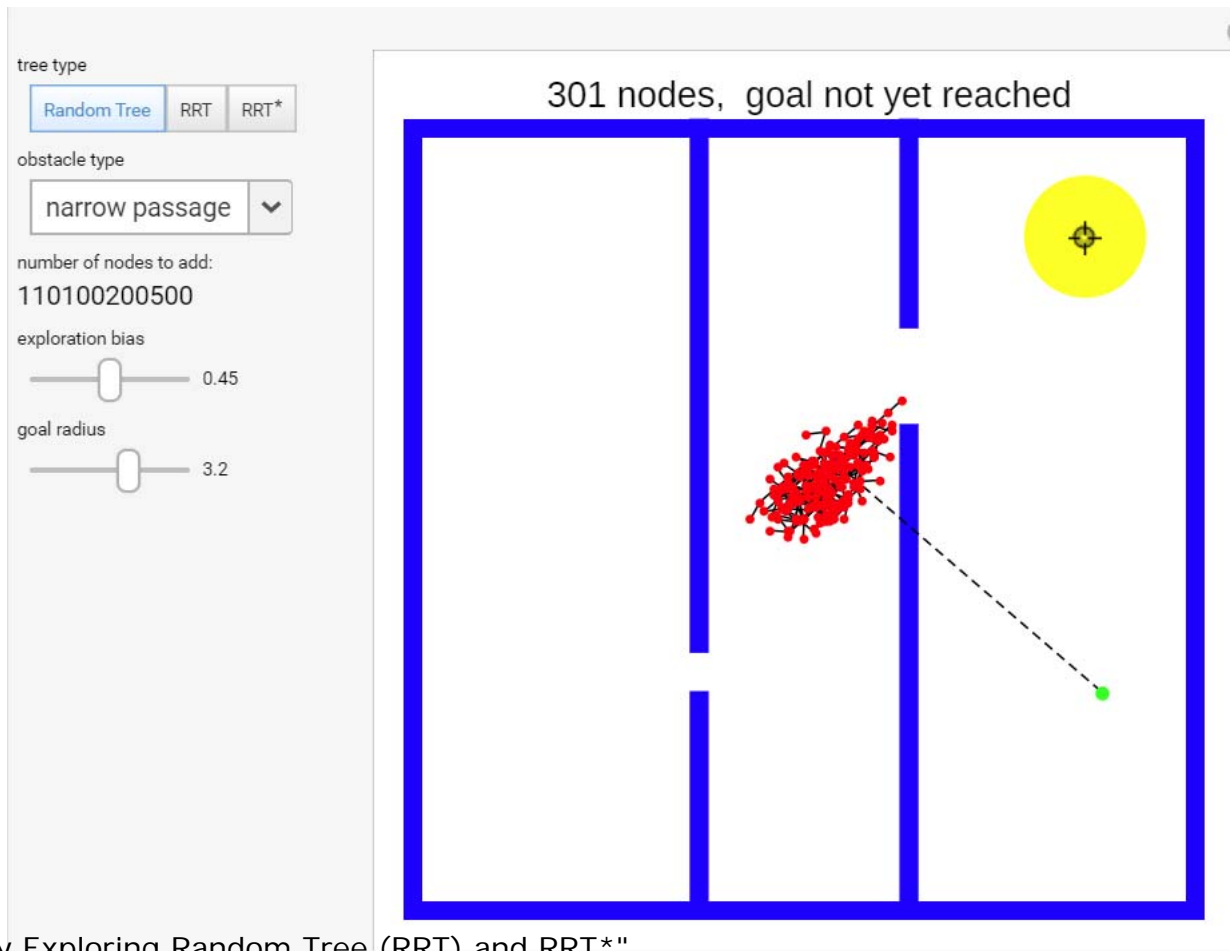
```

1  $V \leftarrow \{x_{init}\}; E \leftarrow \emptyset;$ 
2 for  $i = 1, \dots, n$  do
3    $x_{rand} \leftarrow \text{SampleFree}_i;$ 
4    $x_{nearest} \leftarrow \text{Nearest}(G = (V, E), x_{rand});$ 
5    $x_{new} \leftarrow \text{Steer}(x_{nearest}, x_{rand});$ 
6   if  $\text{ObstacleFree}(x_{nearest}, x_{new})$  then
7      $X_{near} \leftarrow \text{Near}(G =$ 
8        $(V, E), x_{new}, \min\{\gamma_{RRT^*}(\log(\text{card}(V)) /$ 
9          $\text{card}(V)^{1/d}, \eta)\});$ 
10     $V \leftarrow V \cup \{x_{new}\};$ 
11     $x_{min} \leftarrow x_{nearest}; c_{min} \leftarrow$ 
12       $\text{Cost}(x_{nearest}) + c(\text{Line}(x_{nearest}, x_{new}));$ 
13    foreach  $x_{near} \in X_{near}$  do // Connect along a
14      minimum-cost path
15      if
16         $\text{CollisionFree}(x_{near}, x_{new}) \wedge \text{Cost}(x_{near})$ 
17           $+ c(\text{Line}(x_{near}, x_{new})) < c_{min}$  then
18           $x_{min} \leftarrow x_{near}; c_{min} \leftarrow$ 
19             $\text{Cost}(x_{near}) + c(\text{Line}(x_{near}, x_{new}))$ 
20     $E \leftarrow E \cup \{(x_{min}, x_{new})\};$ 
21    foreach  $x_{near} \in X_{near}$  do // Rewire the tree
22      if
23         $\text{CollisionFree}(x_{new}, x_{near}) \wedge \text{Cost}(x_{new})$ 
24           $+ c(\text{Line}(x_{new}, x_{near})) < \text{Cost}(x_{near})$ 
25        then  $x_{parent} \leftarrow \text{Parent}(x_{near});$ 
26         $E \leftarrow (E \setminus \{(x_{parent}, x_{near})\}) \cup \{(x_{new}, x_{near})\}$ 
27 return  $G = (V, E);$ 

```

RT, RRT, RRT*

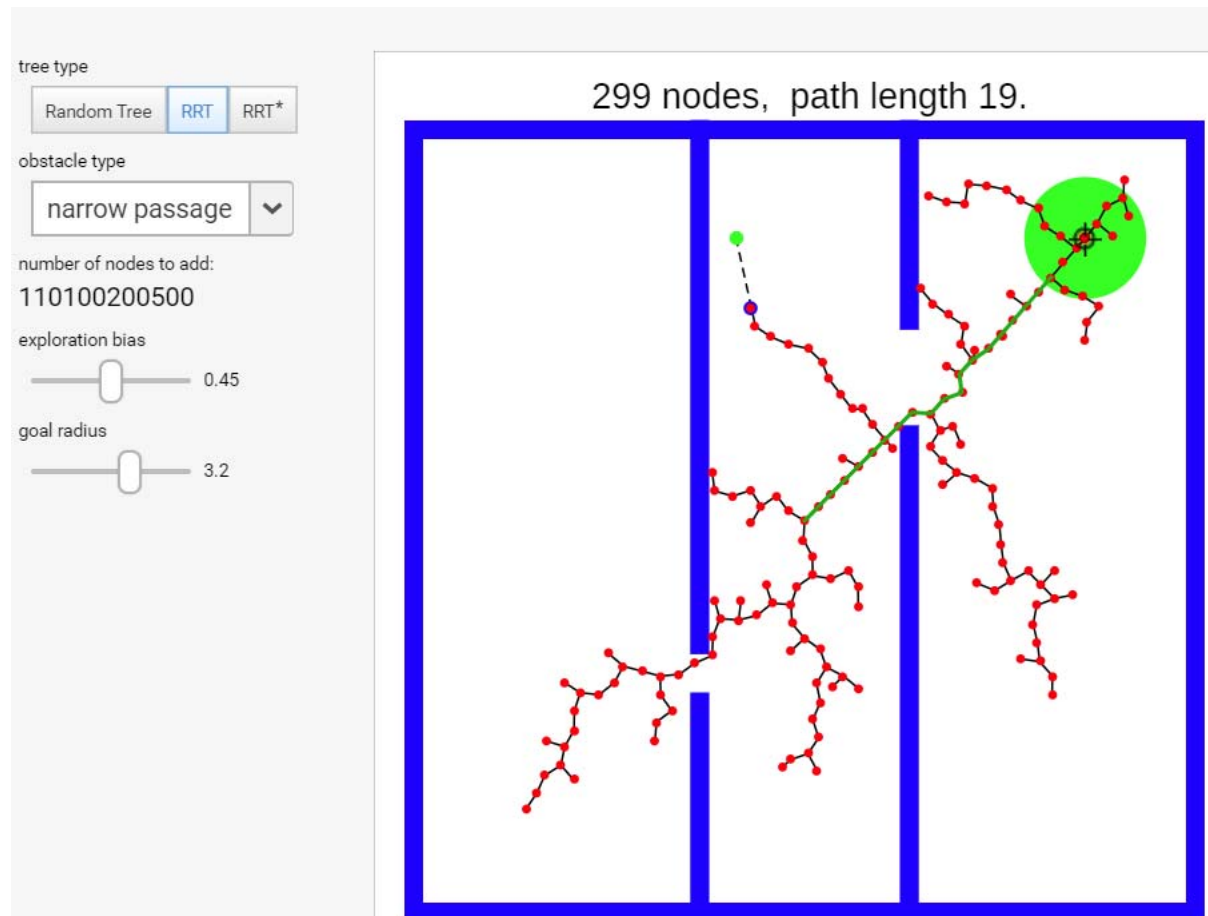
- Simulatore: Random Tree



Li Huang "Rapidly Exploring Random Tree (RRT) and RRT*" <http://demonstrations.wolfram.com/RapidlyExploringRandomTreeRRTAndRRT/>
Wolfram Demonstrations Project

RT, RRT, RRT*

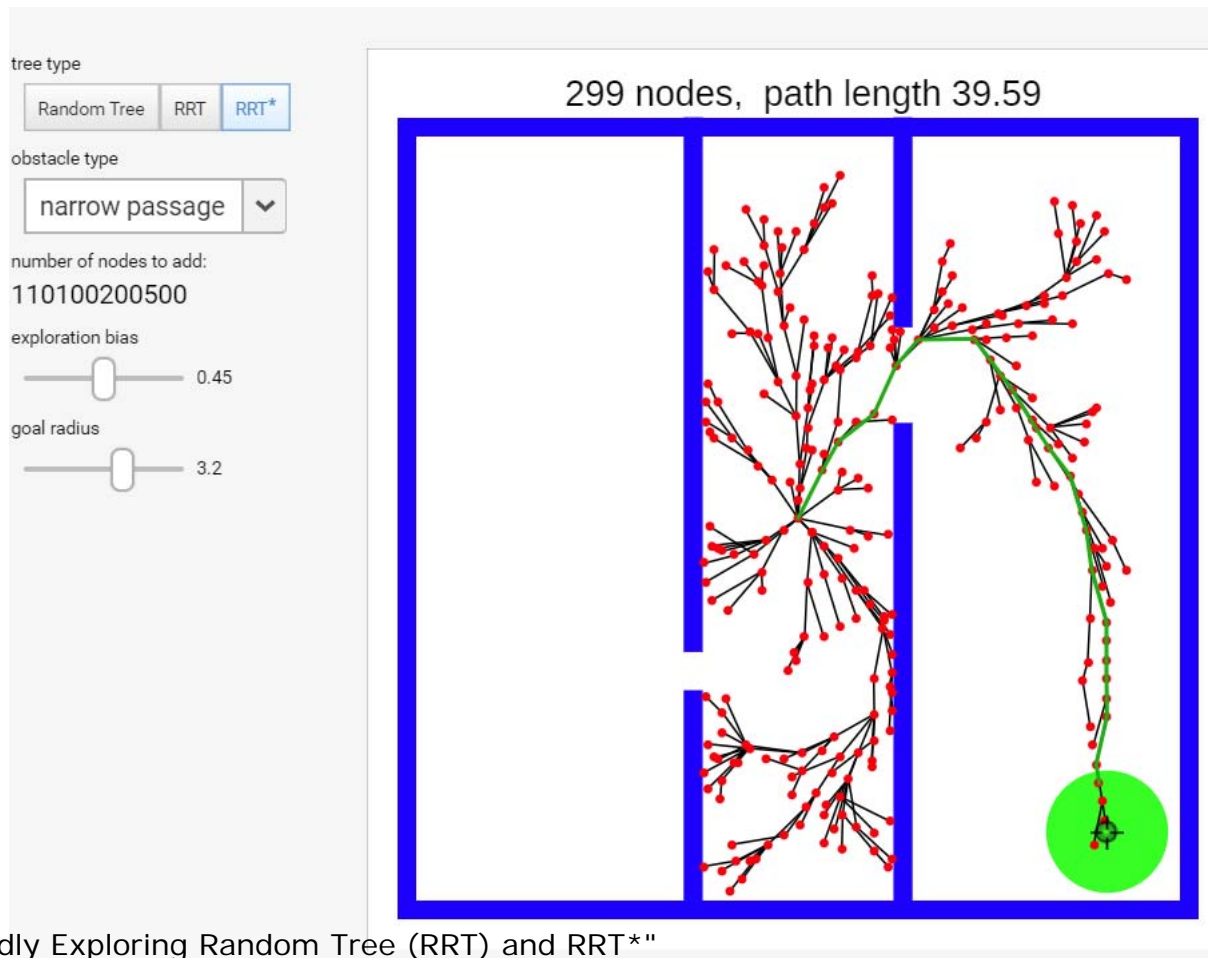
- Simulatore: RRT



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Wolfram Demonstrations Project

RT, RRT, RRT*

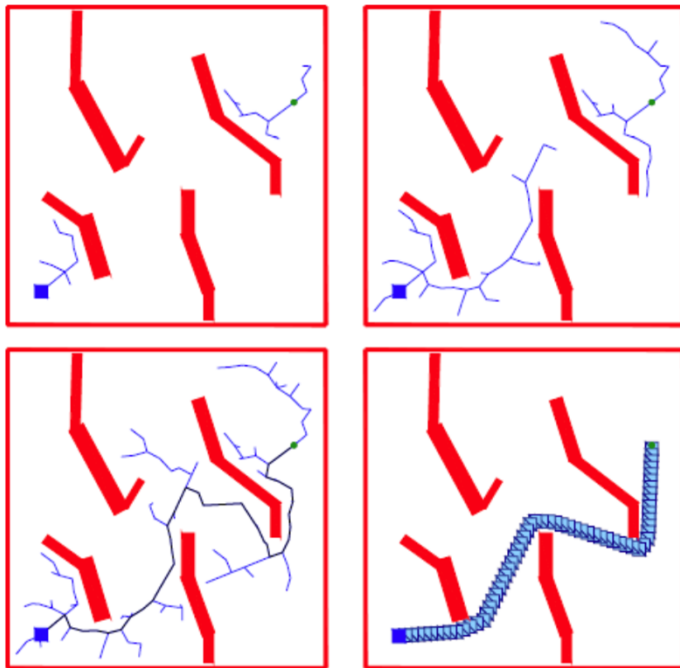
- Simulatore: RRT*



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Wolfram Demonstrations Project

RRT-Connect

- Ricerca dal init e goal
- Extend e Connect



CONNECT(\mathcal{T}, q)

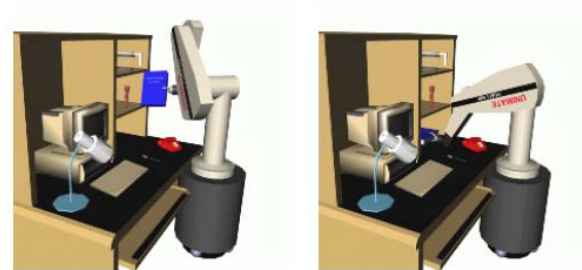
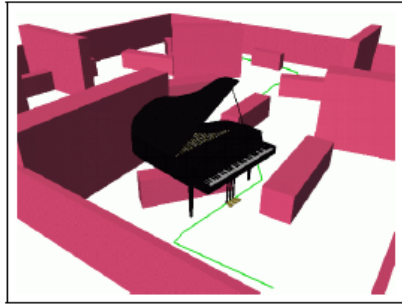
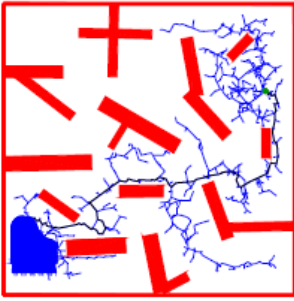
```
1 repeat
2    $S \leftarrow$  EXTEND( $\mathcal{T}, q$ );
3 until not ( $S = Advanced$ )
4 Return  $S$ ;
```

RRT_CONNECT_PLANNER(q_{init}, q_{goal})

```
1  $\mathcal{T}_a.init(q_{init}); \mathcal{T}_b.init(q_{goal});$ 
2 for  $k = 1$  to  $K$  do
3    $q_{rand} \leftarrow$  RANDOM_CONFIG();
4   if not (EXTEND( $\mathcal{T}_a, q_{rand}$ ) = Trapped) then
5     if (CONNECT( $\mathcal{T}_b, q_{new}$ ) = Reached) then
6       Return PATH( $\mathcal{T}_a, \mathcal{T}_b$ );
7   SWAP( $\mathcal{T}_a, \mathcal{T}_b$ );
8 Return Failure
```

RRT-Connect: An Efficient Approach to Single-Query Path Planning. Kuffner and LaValle 2000.

RRT-Connect: Applicazioni



RRT-Connect: An Efficient Approach to Single-Query Path Planning. Kuffner and LaValle 2000.