

I 5-780: Grad AI

Lecture 16: Probability

Geoff Gordon (this lecture)

Tuomas Sandholm

TAs Erik Zawadzki, Abe Othman



Randomness in search

Rapidly-exploring Random Trees

- Break up C-space into Voronoi regions around random landmarks
- Invariant: landmarks always form a tree
 - ▶ known path to root
- Subject to this requirement, placed in a way that tends to split large Voronoi regions
 - ▶ coarse-to-fine search
- Goal: **feasibility** not **optimality** (*)

RRT: required subroutines

- RANDOM_CONFIG
 - ▶ samples from C-space
- EXTEND(\mathbf{q}, \mathbf{q}')
 - ▶ local controller, heads toward \mathbf{q}' from \mathbf{q}
 - ▶ stops before hitting obstacle (and perhaps also after bound on time or distance)
- FIND_NEAREST(\mathbf{q}, Q)
 - ▶ searches current tree Q for point near \mathbf{q}

Path Planning with RRTs

RRT = Rapidly-Exploring Random Tree

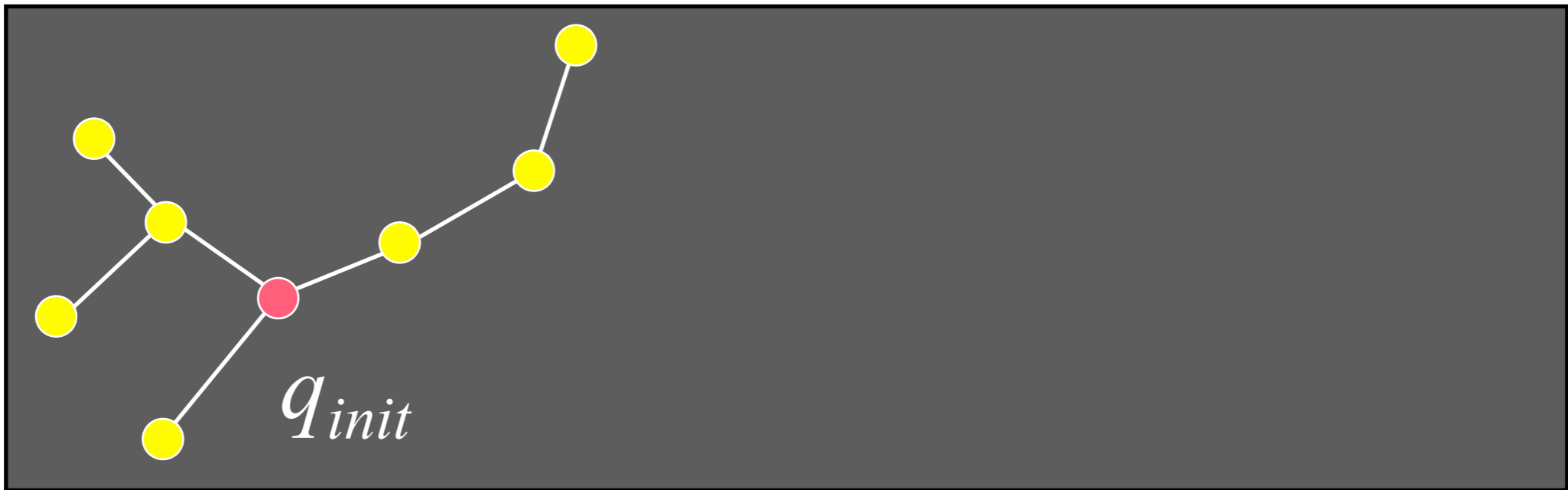


```
BUILT_RRT( $q_{init}$ ) {  
   $T = q_{init}$   
  for  $k = 1$  to  $K$  {  
     $q_{rand} = \text{RANDOM\_CONFIG}()$   
     $\text{EXTEND}(T, q_{rand});$   
  }  
}
```

```
 $\text{EXTEND}(T, q)$  {  
   $q_{near} = \text{FIND\_NEAREST}(q, T)$   
   $q_{new} = \text{EXTEND}(q_{near}, q)$   
   $T = T + (q_{near}, q_{new})$   
}
```

Path Planning with RRTs

RRT = Rapidly-Exploring Random Tree

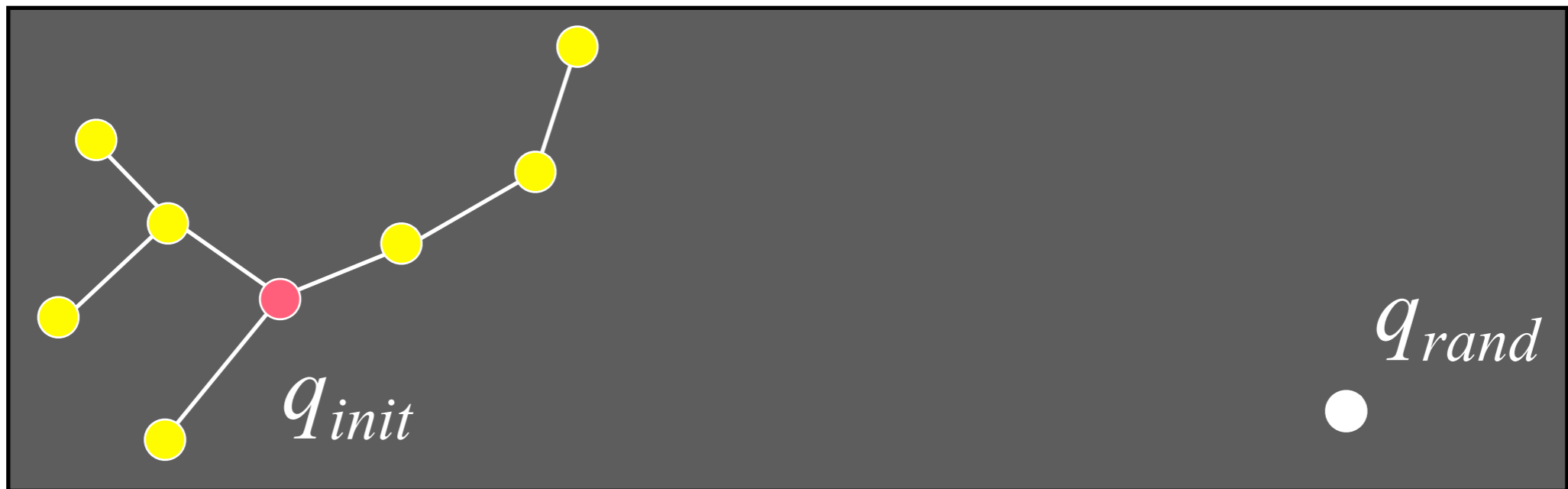


```
BUILT_RRT( $q_{init}$ ) {  
   $T = q_{init}$   
  for  $k = 1$  to  $K$  {  
     $q_{rand} = \text{RANDOM\_CONFIG}()$   
     $\text{EXTEND}(T, q_{rand});$   
  }  
}
```

```
 $\text{EXTEND}(T, q)$  {  
   $q_{near} = \text{FIND\_NEAREST}(q, T)$   
   $q_{new} = \text{EXTEND}(q_{near}, q)$   
   $T = T + (q_{near}, q_{new})$   
}
```

Path Planning with RRTs

RRT = Rapidly-Exploring Random Tree

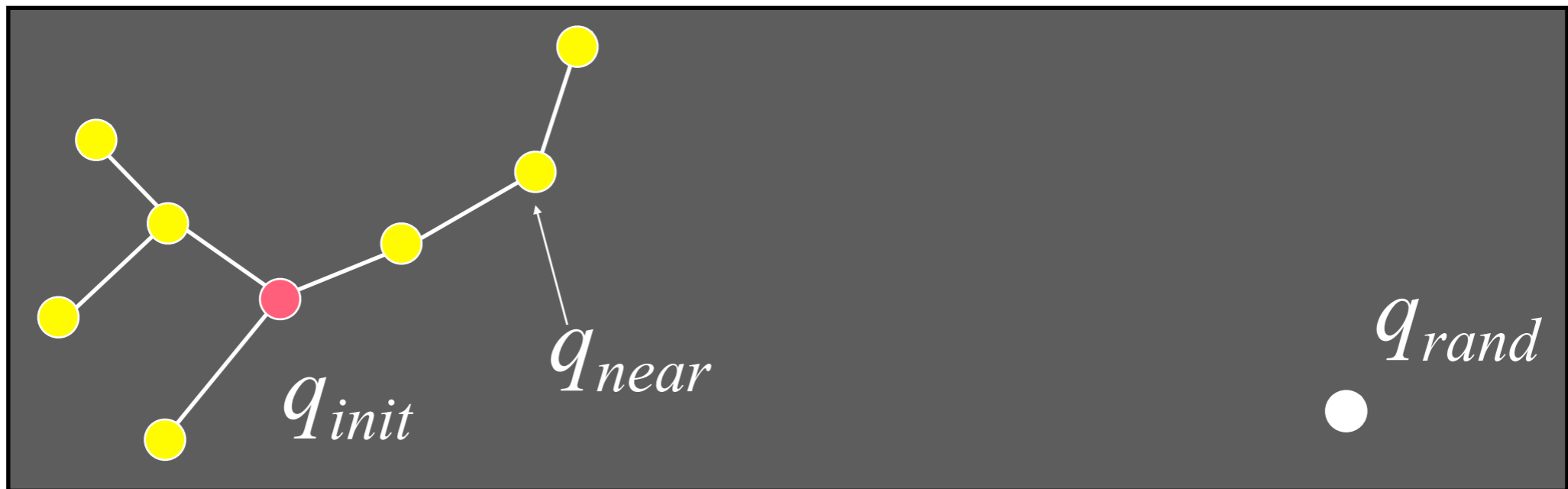


```
BUILT_RRT( $q_{init}$ ) {  
   $T = q_{init}$   
  for  $k = 1$  to  $K$  {  
     $q_{rand} = \text{RANDOM\_CONFIG}()$   
     $\text{EXTEND}(T, q_{rand});$   
  }  
}
```

```
 $\text{EXTEND}(T, q)$  {  
   $q_{near} = \text{FIND\_NEAREST}(q, T)$   
   $q_{new} = \text{EXTEND}(q_{near}, q)$   
   $T = T + (q_{near}, q_{new})$   
}
```

Path Planning with RRTs

RRT = Rapidly-Exploring Random Tree

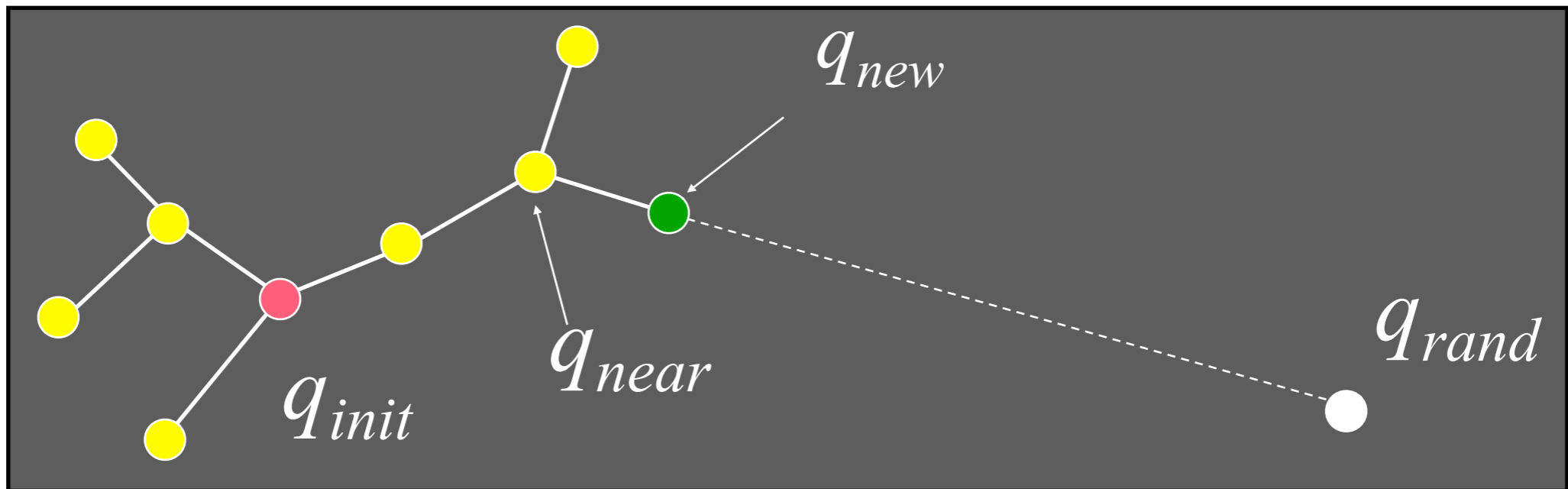


```
BUILT_RRT( $q_{init}$ ) {  
   $T = q_{init}$   
  for  $k = 1$  to  $K$  {  
     $q_{rand} = \text{RANDOM\_CONFIG}()$   
     $\text{EXTEND}(T, q_{rand});$   
  }  
}
```

```
EXTEND( $T, q$ ) {  
   $q_{near} = \text{FIND\_NEAREST}(q, T)$   
   $q_{new} = \text{EXTEND}(q_{near}, q)$   
   $T = T + (q_{near}, q_{new})$   
}
```

Path Planning with RRTs

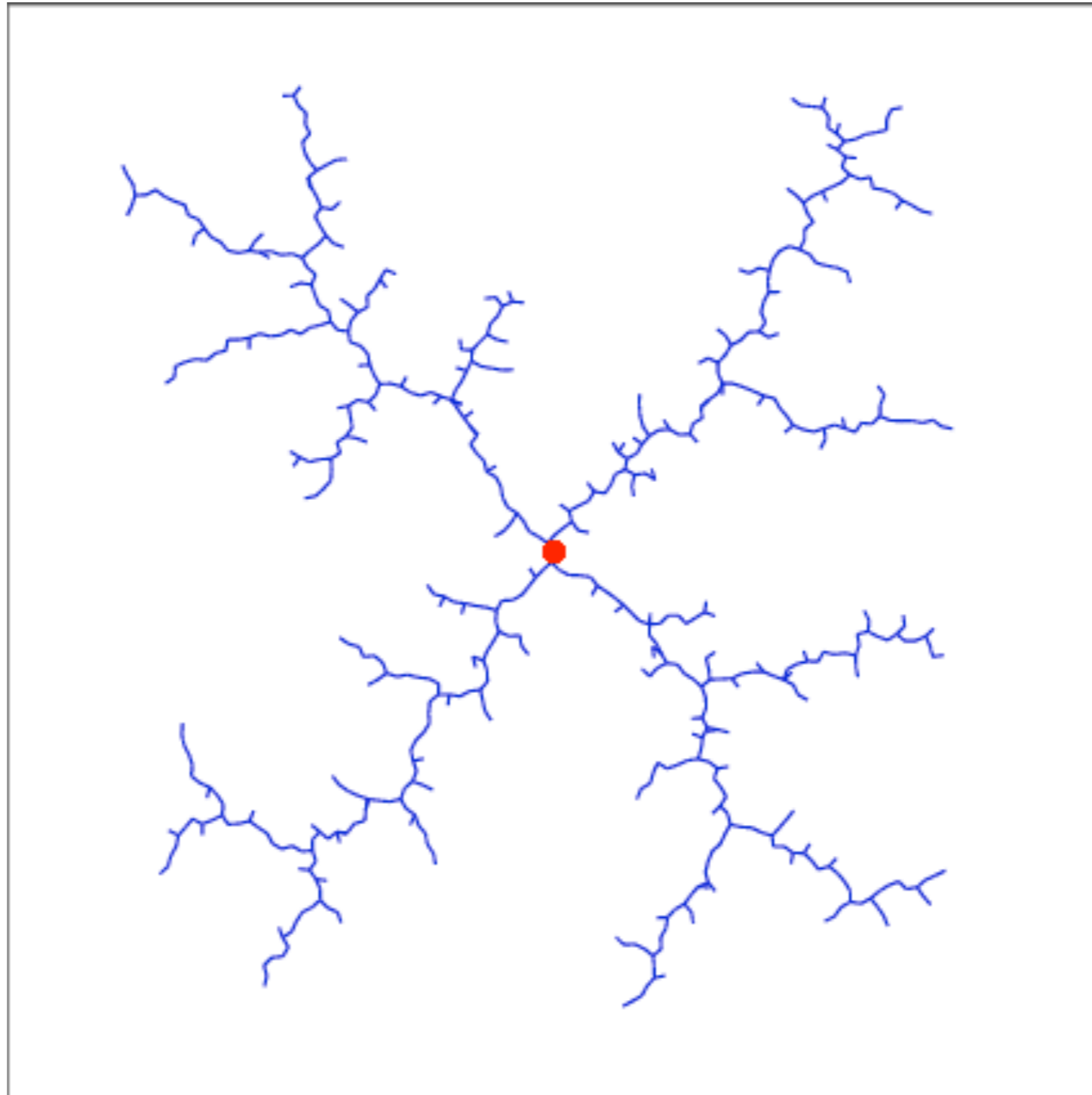
RRT = Rapidly-Exploring Random Tree



```
BUILT_RRT( $q_{init}$ ) {  
   $T = q_{init}$   
  for  $k = 1$  to  $K$  {  
     $q_{rand} = \text{RANDOM\_CONFIG}()$   
     $\text{EXTEND}(T, q_{rand});$   
  }  
}
```

```
 $\text{EXTEND}(T, q)$  {  
   $q_{near} = \text{FIND\_NEAREST}(q, T)$   
   $q_{new} = \text{EXTEND}(q_{near}, q)$   
   $T = T + (q_{near}, q_{new})$   
}
```

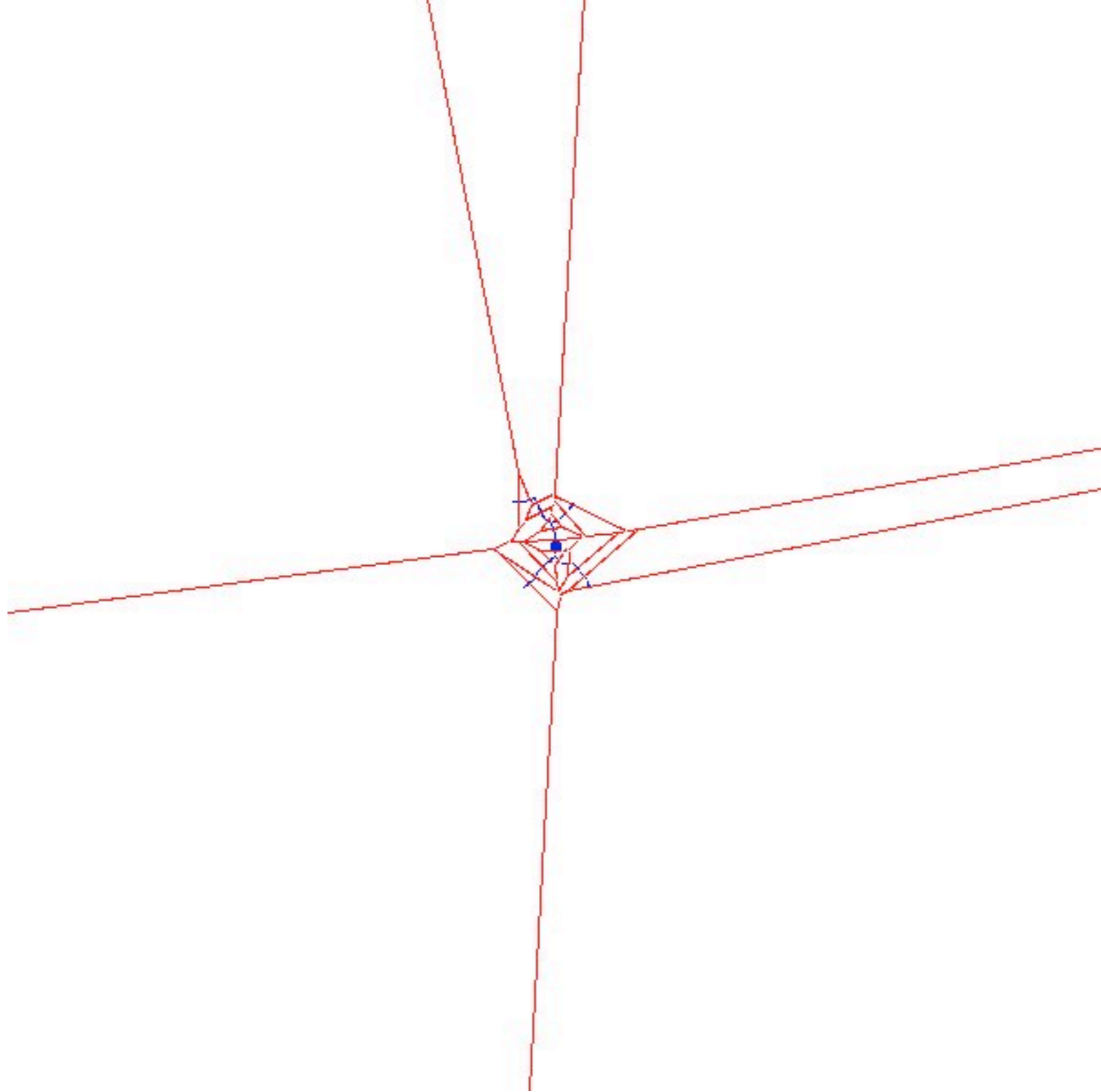
RRT example

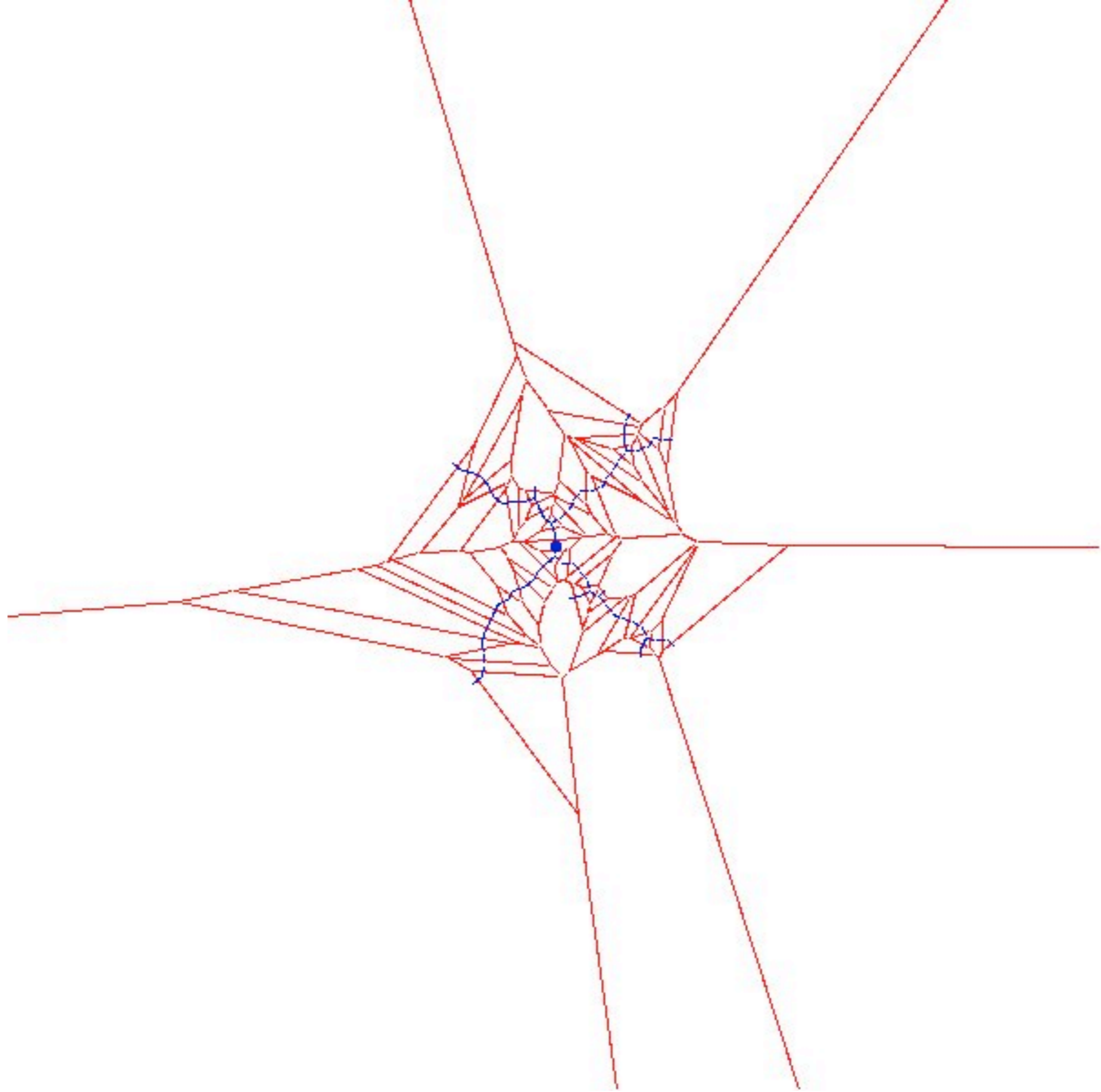


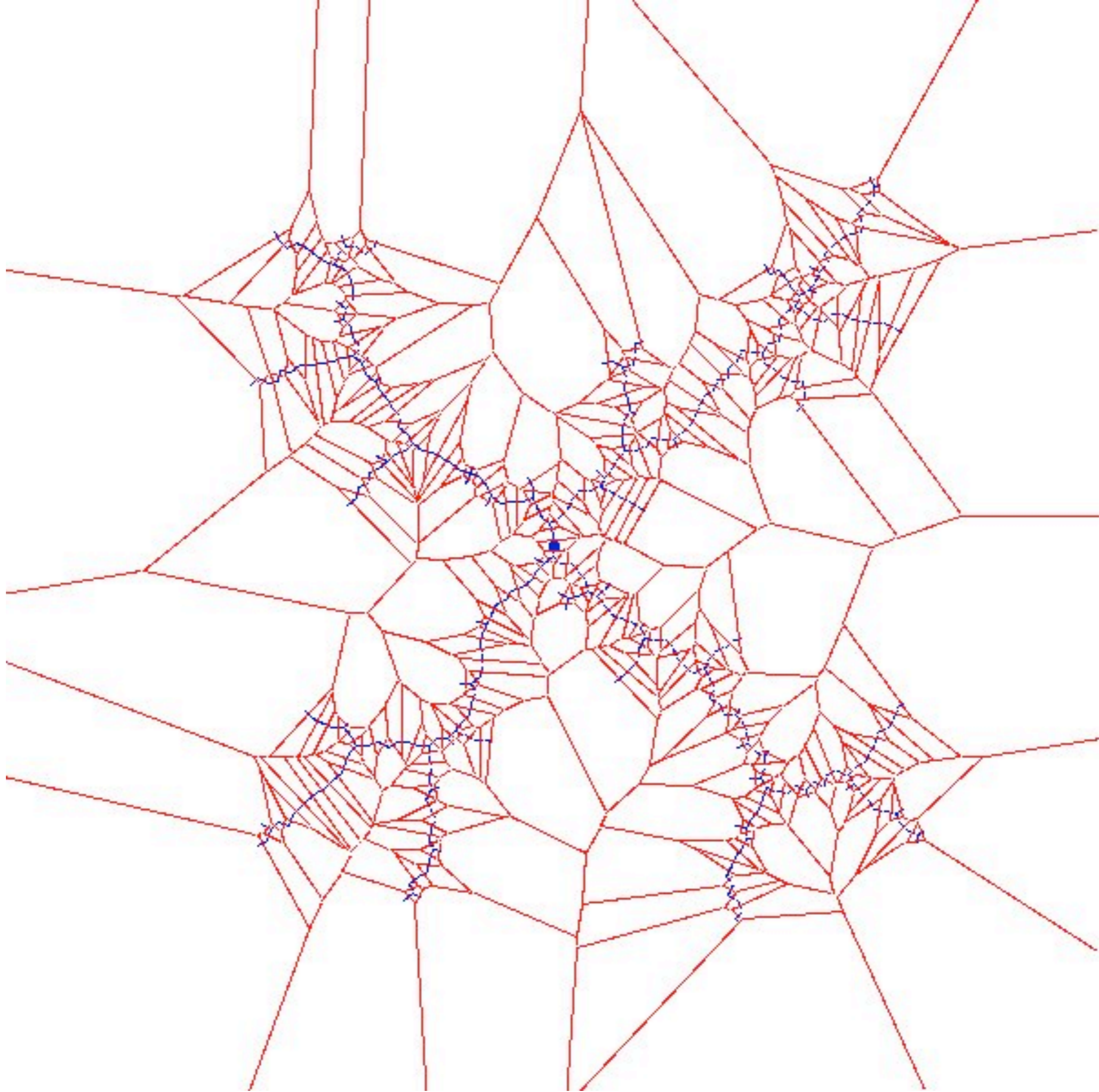
Planar holonomic robot

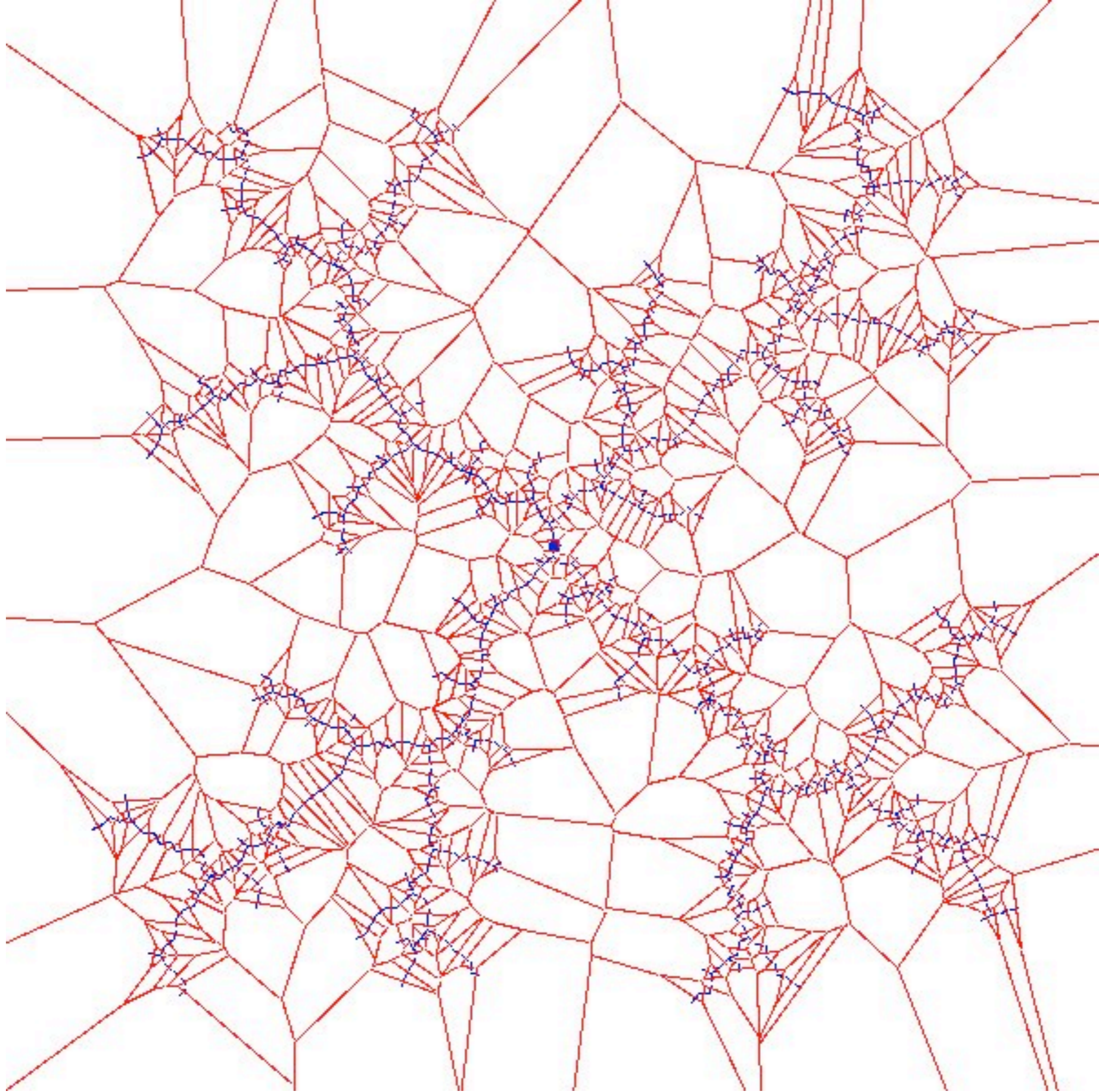
RRTs explore coarse to fine

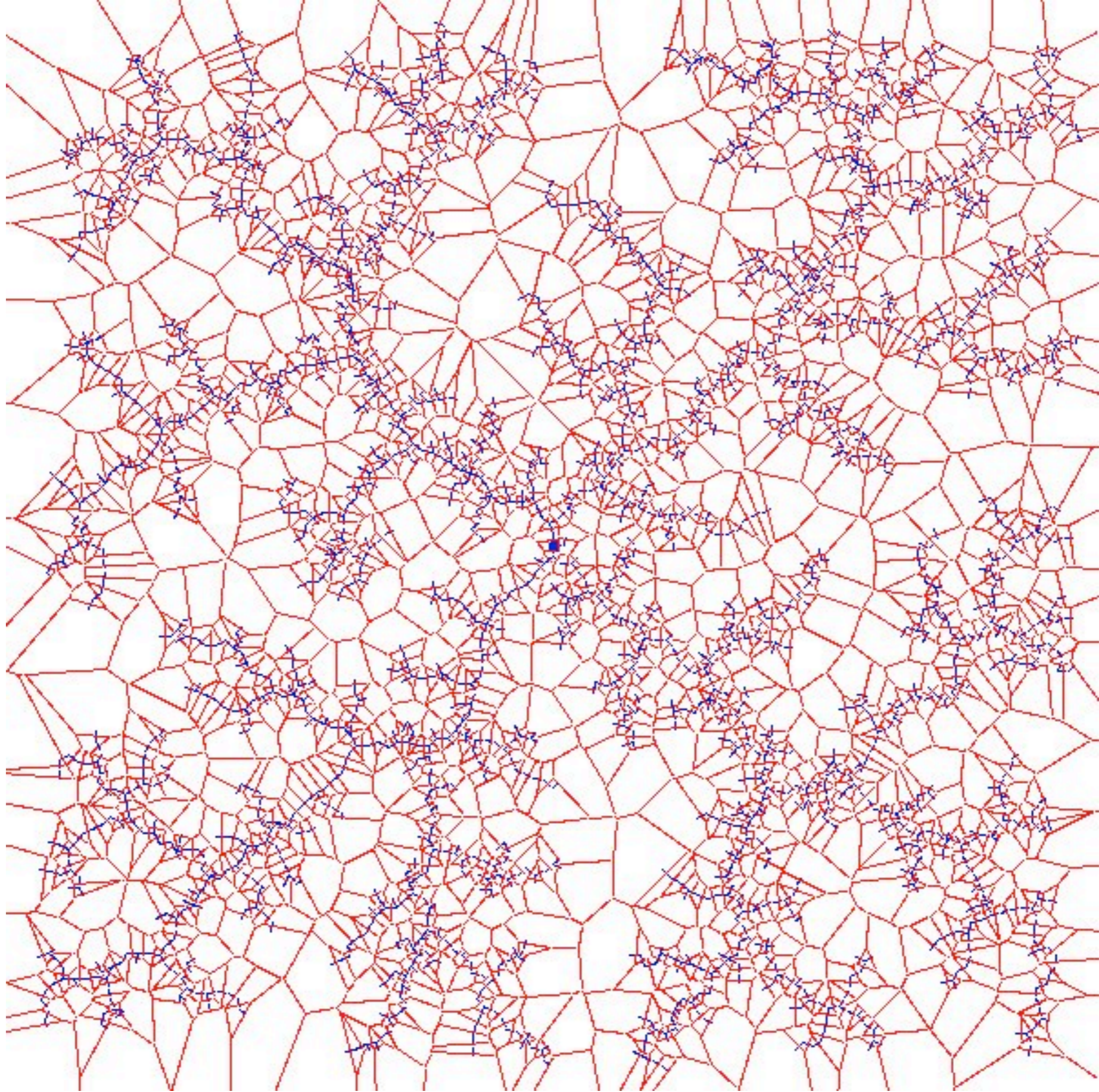
- Tend to break up large Voronoi regions
 - ▶ higher probability of q_{rand} being in them
- Limiting distribution of vertices given by RANDOM_CONFIG
 - ▶ as RRT grows, probability that q_{rand} is reachable with local controller (and so immediately becomes a new vertex) approaches 1



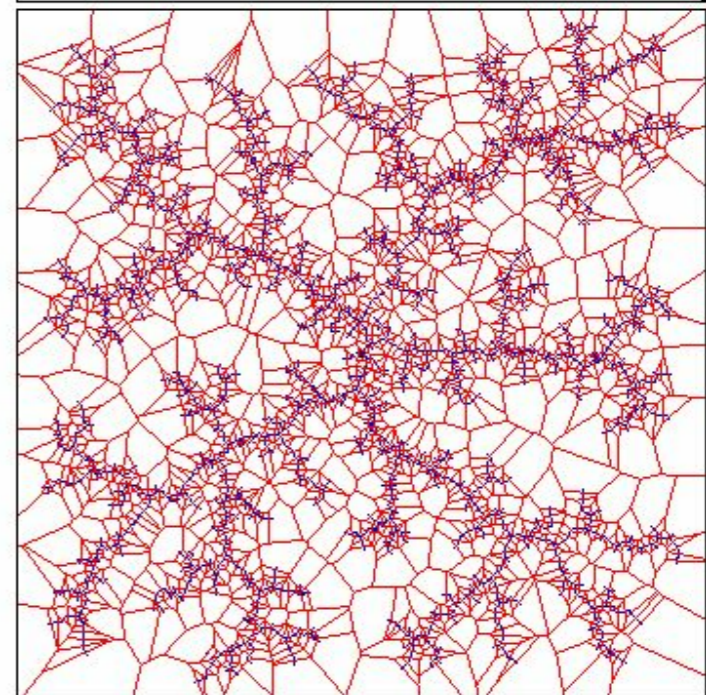
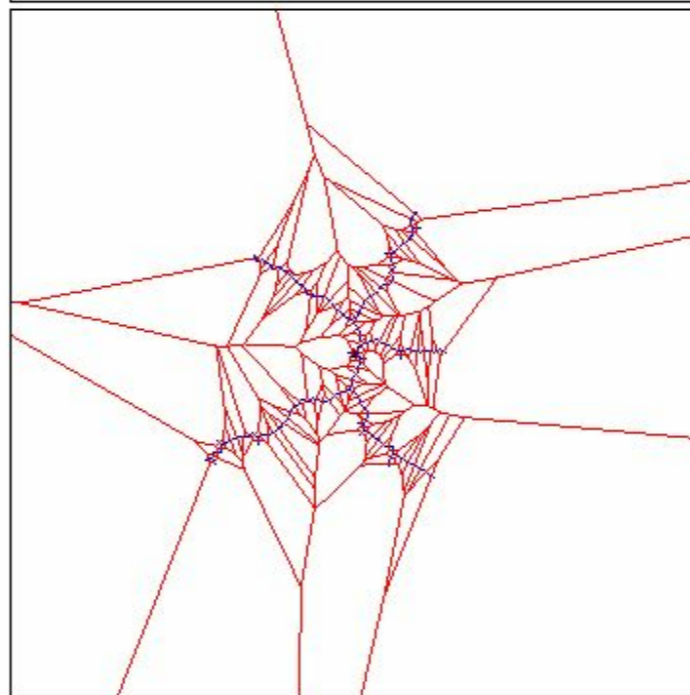
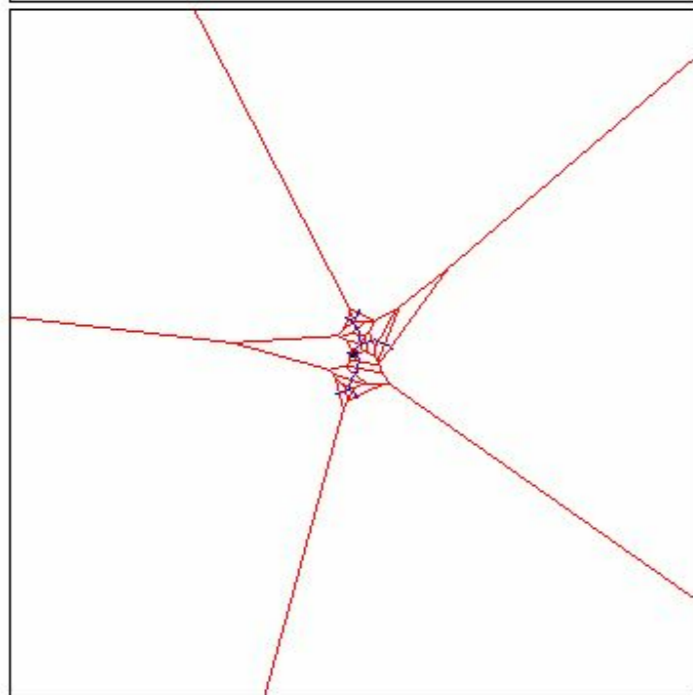
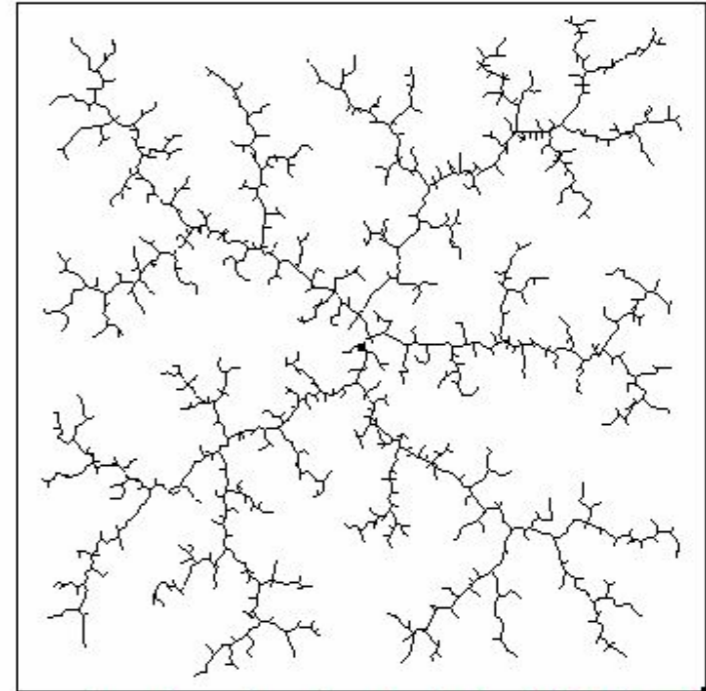
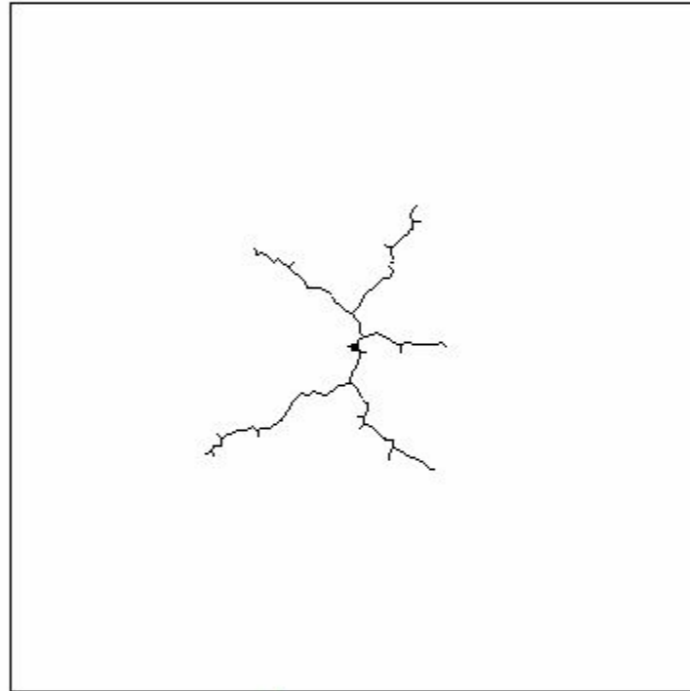
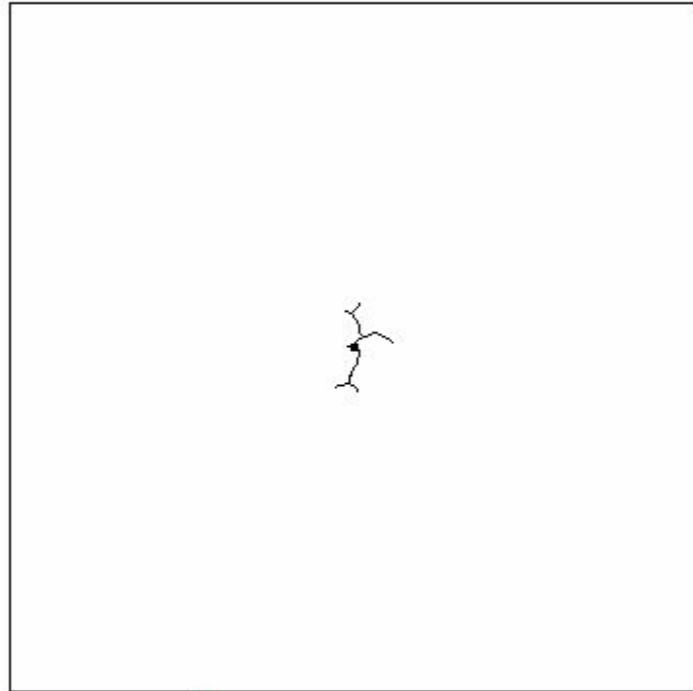




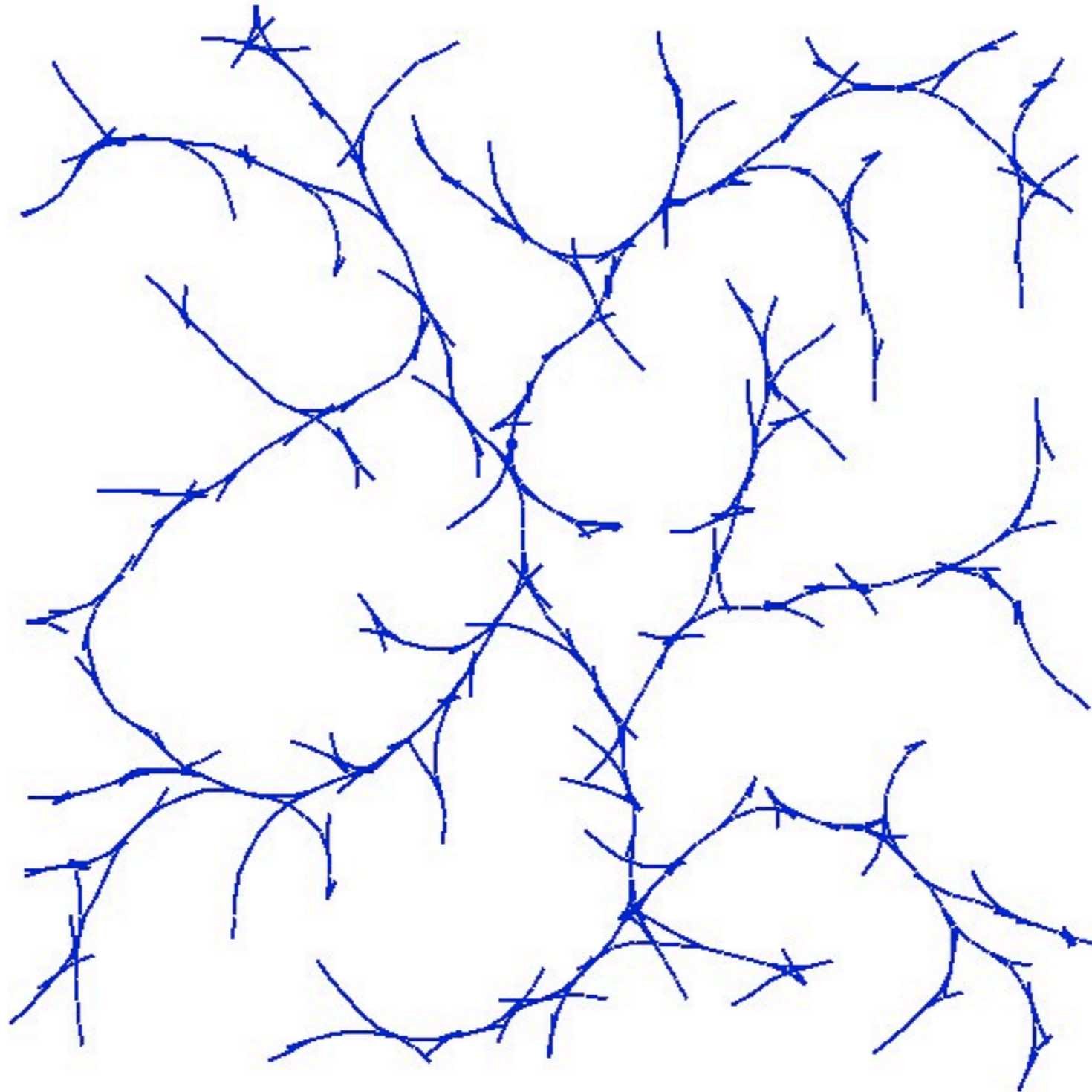




RRT example



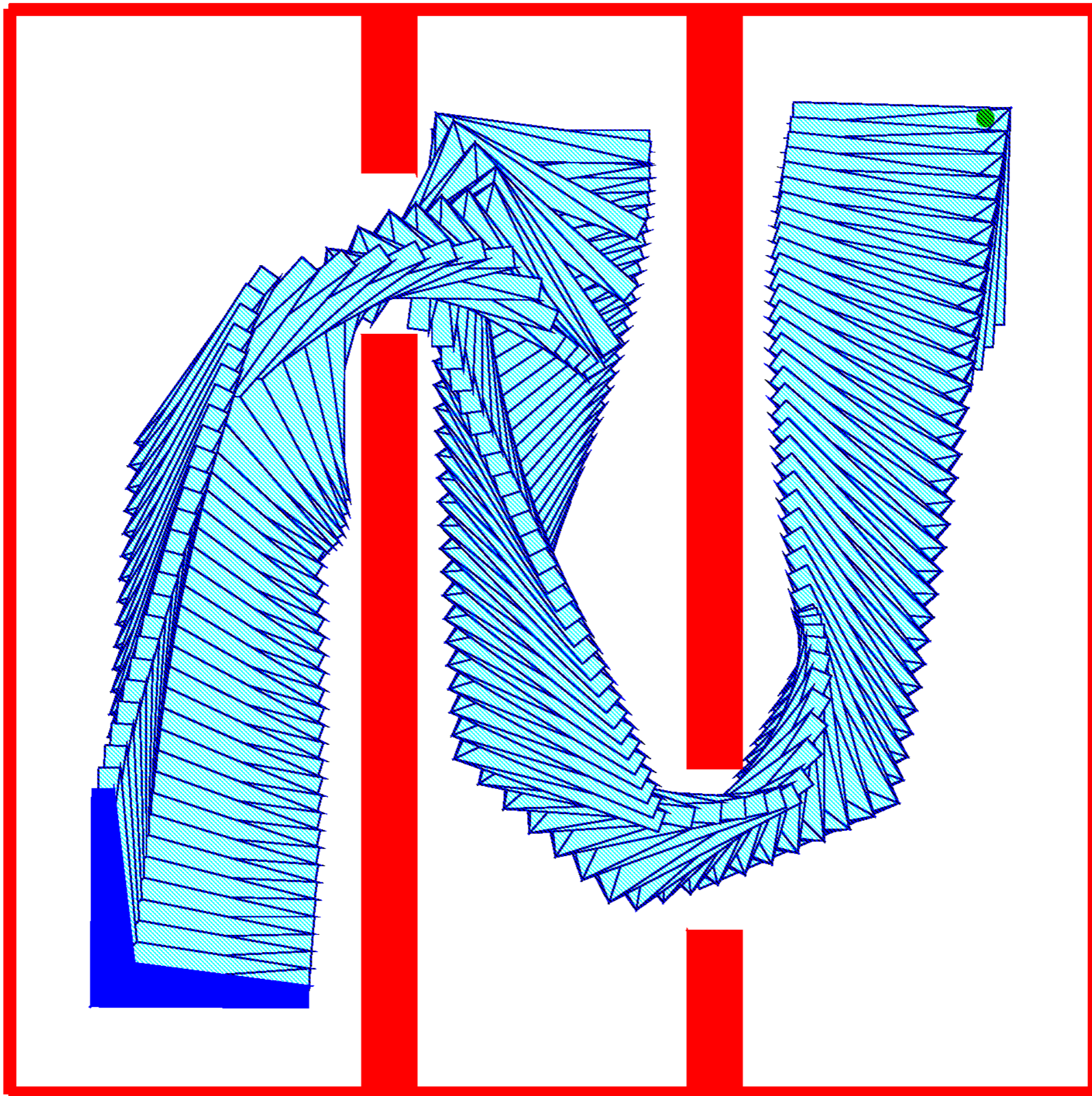
RRT for a car (3 dof)

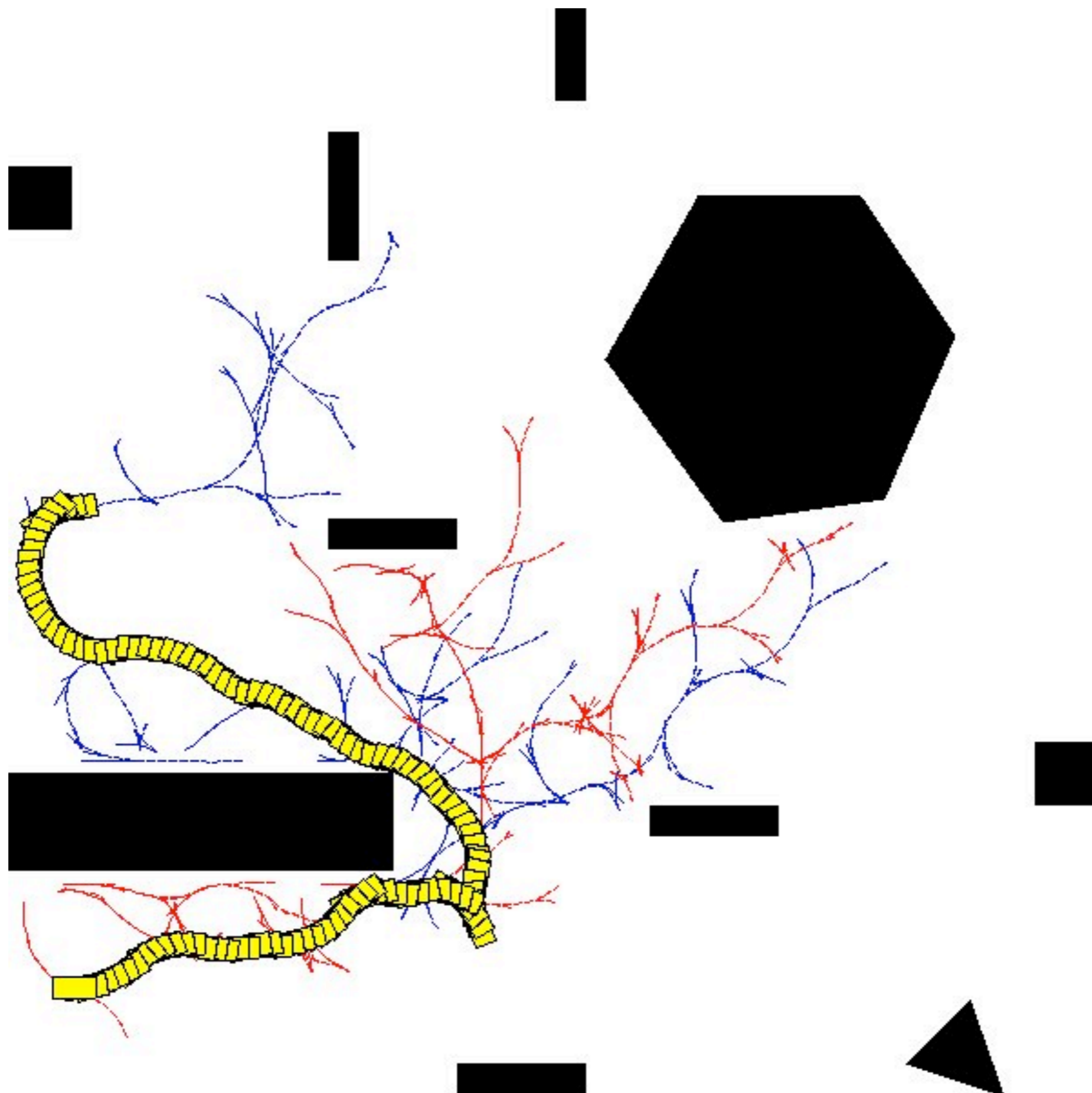


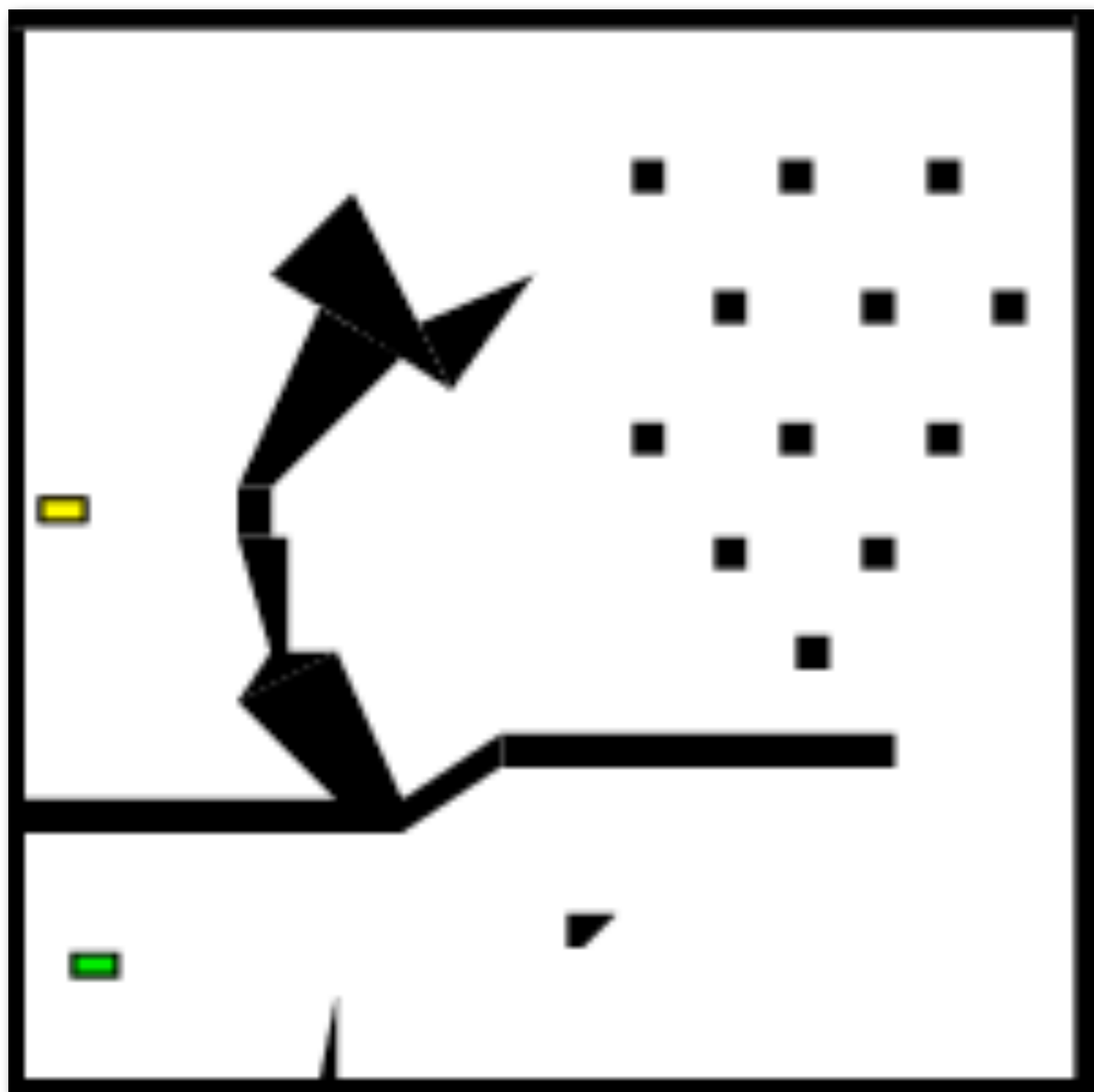
Planning with RRTs

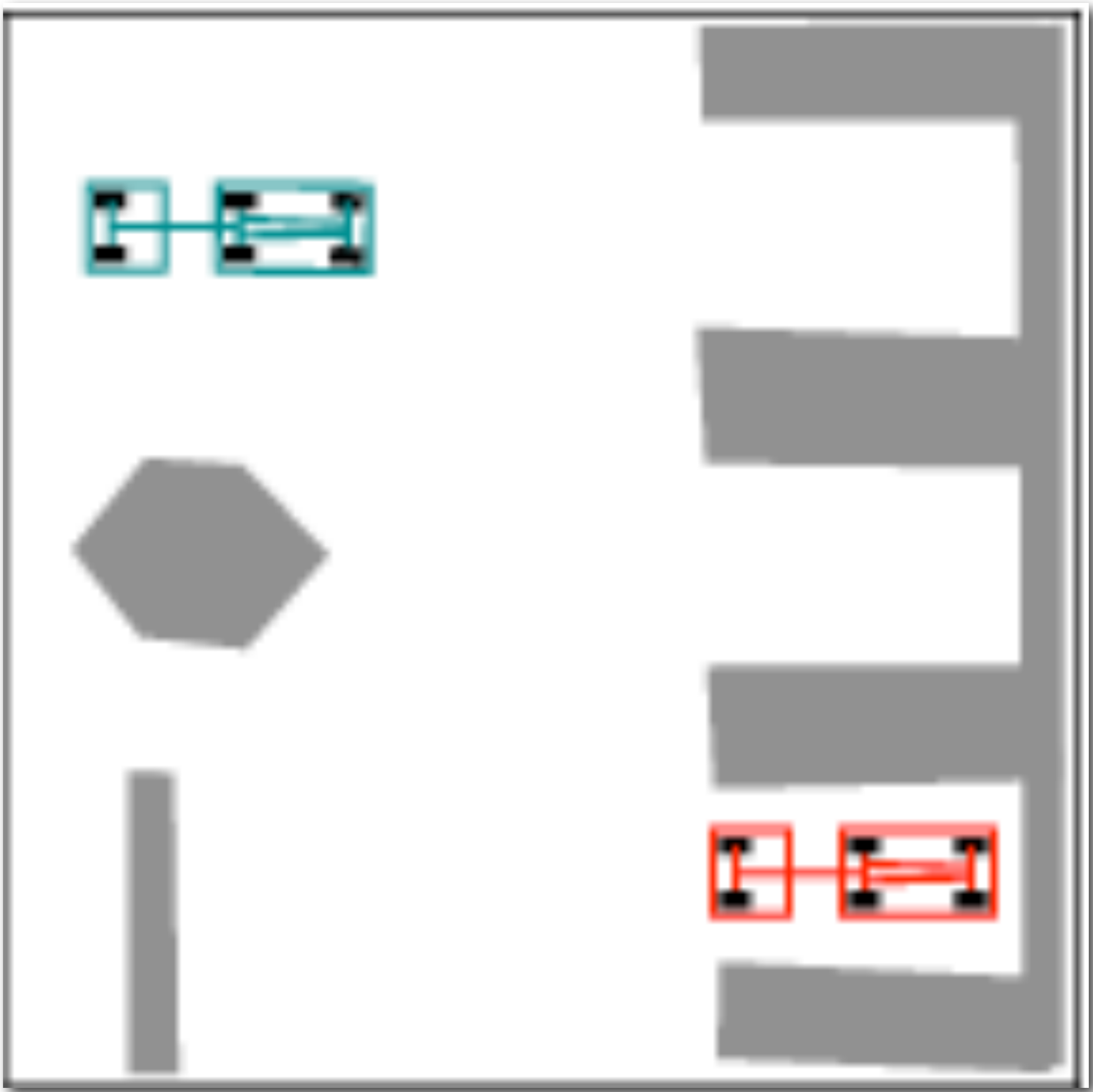


- Build RRT from start until we add a node that can reach goal using local controller
- (Unique) path: root \rightarrow last node \rightarrow goal
- Optional: “rewire” tree during growth by testing connectivity to more than just closest node
- Optional: grow forward and backward











Probability

Probability



- Random variables
- Atomic events
- Sample space

Probability



- Events
- Combining events

Probability



- Measure:
 - ▶ disjoint union:
 - ▶ e.g.:
 - ▶ interpretation:
- Distribution:
 - ▶ interpretation:
 - ▶ e.g.:

Example

		AAPL price		
Weather		up	same	down
	sun	0.09	0.15	0.06
	rain	0.21	0.35	0.14

Bigger example

		AAPL price			
PIT	Weather		up	same	dow
		sun	0.03	0.05	0.02
		rain	0.07	0.12	0.05
LAX	Weather		up	same	dow
		sun	0.14	0.23	0.09
		rain	0.06	0.10	0.04

Notation

- $X=x$: event that r.v. X is realized as value x
- $P(X=x)$ means probability of event $X=x$
 - ▶ if clear from context, may omit “ $X=$ ”
 - ▶ instead of $P(\text{Weather}=\text{rain})$, just $P(\text{rain})$
 - ▶ complex events too: e.g., $P(X=x, Y \neq y)$
- $P(X)$ means a function: $x \rightarrow P(X=x)$

Functions of RVs

- Extend definition: any deterministic function of RVs is also an RV
- E.g., “profit”:

		AAPL price		
Weather		up	same	down
	sun	-11	0	11
	rain	-11	0	11

Sample v. population

- Suppose we watch for 100 days and count up our observations

		AAPL price		
Weather		up	same	dow
	sun	0.09	0.15	0.06
	rain	0.21	0.35	0.14

		AAPL price		
Weather		up	same	dow
	sun	7	12	3
	rain	22	41	15

Law of large numbers

(simple version)

- If we take a sample of size N from distribution P , count up frequencies of atomic events, and normalize (divide by N) to get a distribution \tilde{P}
- Then $\tilde{P} \rightarrow P$ as $N \rightarrow \infty$

Working w/ distributions



- Marginals (eliminate an irrelevant RV)
- Conditionals (incorporate an observation)
- Joint (before marginalizing or conditioning)

Marginals

		AAPL price		
Weather		up	same	down
	sun	0.09	0.15	0.06
	rain	0.21	0.35	0.14

Law of total probability

also called “sum rule”

- Two RVs, X and Y
- Y has values y_1, y_2, \dots, y_k
- $P(X) = P(X, Y=y_1) + P(X, Y=y_2) + \dots$

Conditioning on an observation

- Two steps:
 - ▶ enforce consistency
 - ▶ renormalize
- Notation:

	Coin	
	H	T
Weather	sun	0.15
	rain	0.35

Conditionals

AAPL price

PIT
Weather

	up	same	down
sun	0.03	0.05	0.02
rain	0.07	0.12	0.05

LAX
Weather

	up	same	down
sun	0.14	0.23	0.09
rain	0.06	0.10	0.04

Conditionals



- Thought experiment: what happens if we condition on an event of zero probability?

Notation

- $P(X | Y)$ is a function: $x, y \rightarrow P(X=x | Y=y)$
- So:
 - ▶ $P(X | Y) P(Y)$ means the function
 $x, y \rightarrow$

Conditionals in literature



When you have eliminated the impossible,
whatever remains, however improbable, must be
the truth.

—*Sir Arthur Conan Doyle, as Sherlock Holmes*

Exercise



\$\$\$\$

Exercise

