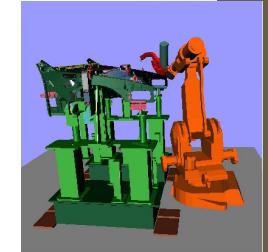
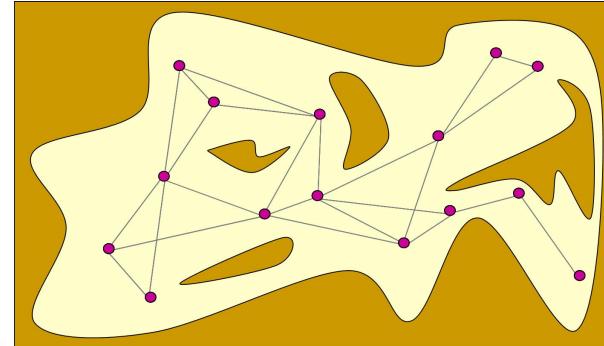


## Tree-Growing Sample-Based Motion Planning

### Tree-growing planners

- Idea: grow a **tree** of feasible paths from the start until it reaches a neighborhood of the goal
  - *Sampling bias* toward “boundary” of currently explored region, helps especially if the start is in a region with poor visibility
- Many variants:
  - Rapidly-exploring Random Trees (RRTs) are popular, easy to implement (LaValle and Kuffner 2001)
  - Expansive space trees (ESTs) use a different sampling strategy (Hsu et al 2001)
  - SBL (Single-query, Bidirectional, Lazy planner) often efficient in practice (Sanchez-Ante and Latombe, 2005)

## Probabilistic Roadmaps

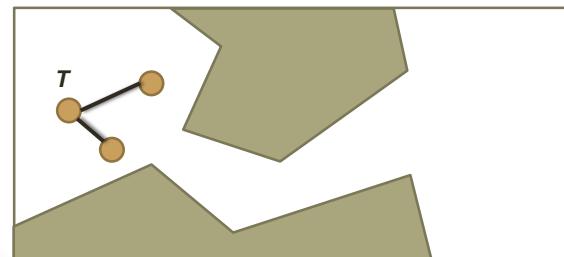


What if only a small portion of the space needs to be explored?

What if omnidirectional motion in C-space is not permitted?

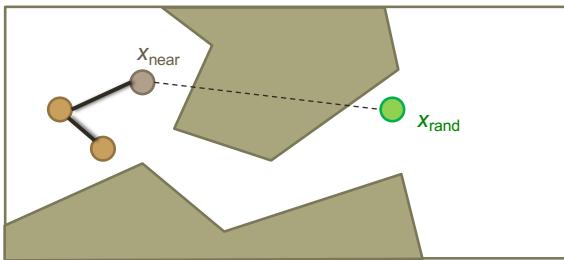
## RRT

- Build a tree  $T$  of configurations, starting at  $x_{\text{start}}$
- Extend:
  - Sample a configuration  $x_{\text{rand}}$  from  $C$  at random
  - Find the node  $x_{\text{near}}$  in  $T$  that is closest to  $x_{\text{rand}}$
  - Extend a short path from  $x_{\text{near}}$  toward  $x_{\text{rand}}$



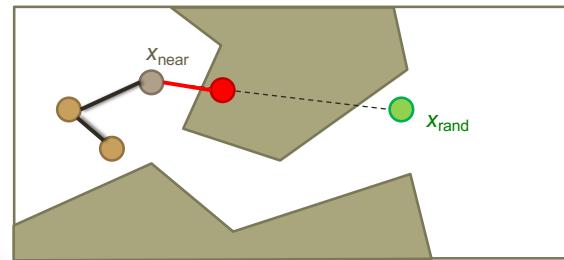
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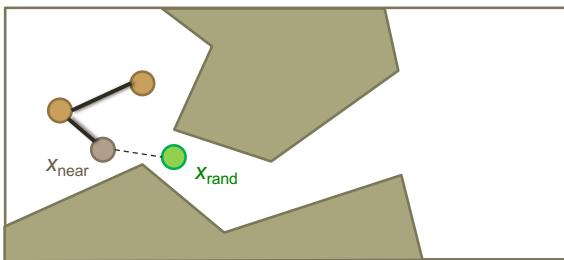
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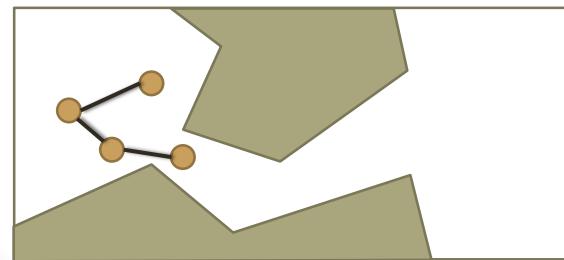
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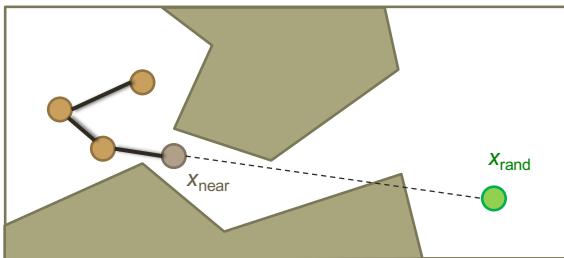
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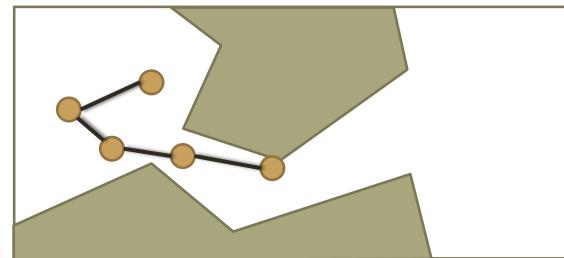
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- Build a tree  $T$  of configurations, starting at  $x_{\text{start}}$
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# RRT

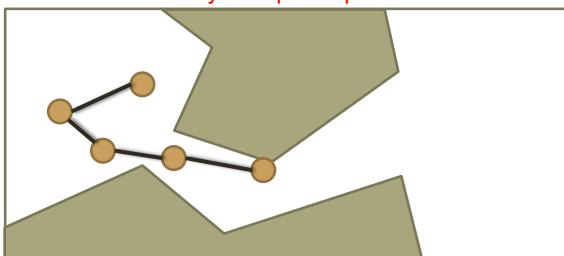
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- Extend:
  - Sample a configuration  $x_{\text{rand}}$  from  $C$  at random
  - Find the node  $x_{\text{near}}$  in  $T$  that is closest to  $x_{\text{rand}}$
  - Extend a **short** path from  $x_{\text{near}}$  toward  $x_{\text{rand}}$

Governed by a step size parameter  $\delta$

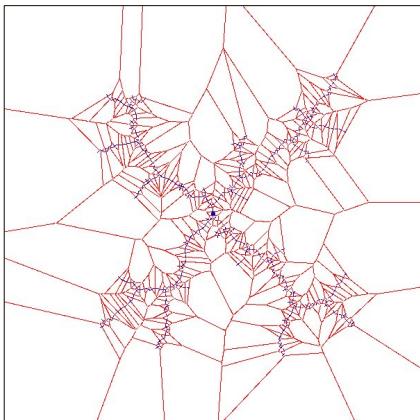


# Implementation Details

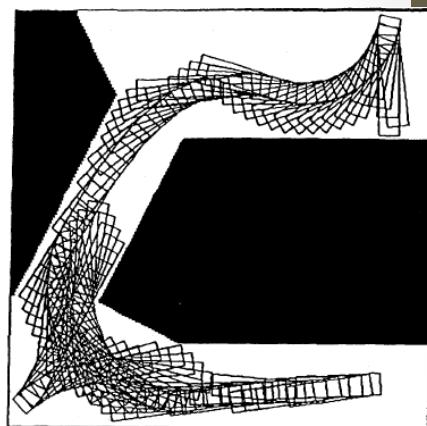
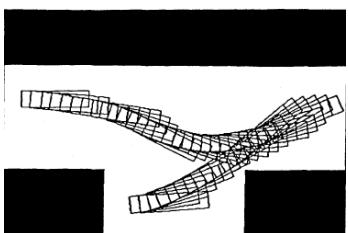
- Bottleneck: finding nearest neighbor each step
  - $O(n)$  with naïve implementation  $\Rightarrow O(n^2)$  overall
  - KD tree data structure  $O(n^{1-1/d})$
  - Approximate nearest neighbors often very effective
- Terminate when extension reaches a goal set
  - Usually visibility set of goal configuration
- Bidirectional strategy
  - Grow a tree from goal as well as start, connect when closest nodes in either tree can “see” each other

## What is the sampling strategy?

- Probability that a node gets selected for expansion is proportional to the volume of its Voronoi cell



## Paths for a Car-Like Robot



## Planning with Differential Constraints

(Kinodynamic Planning)

## Setting

- Differential constraints
- Dynamics, nonholonomic systems

$$\frac{dq}{dt} = \sum_k f_k(q) u_k$$

↑                   ↑  
Vector fields      Controls

We'll consider fewer control dimensions than state dimensions

## Example: 1D Point Mass

- Mass M



- 2D configuration space (state space)
- Controlled force  $f$
- Equations of motion:

$$\begin{aligned} \dot{x}/dt &= v \\ \dot{v}/dt &= f / M \end{aligned}$$

## Example: 1D Point Mass

## Example: 1D Point Mass



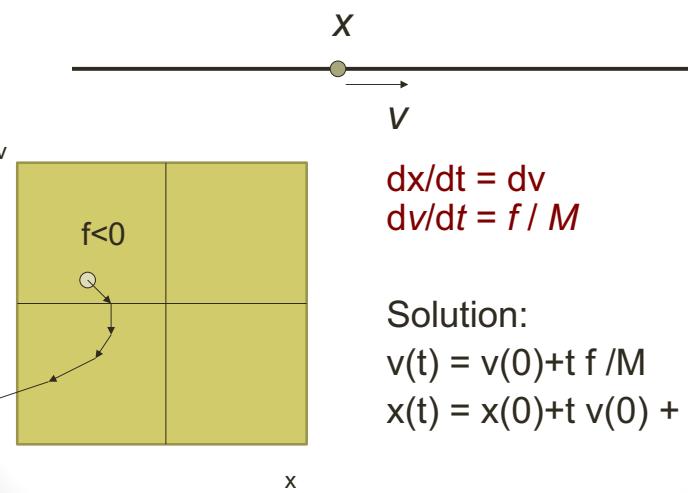
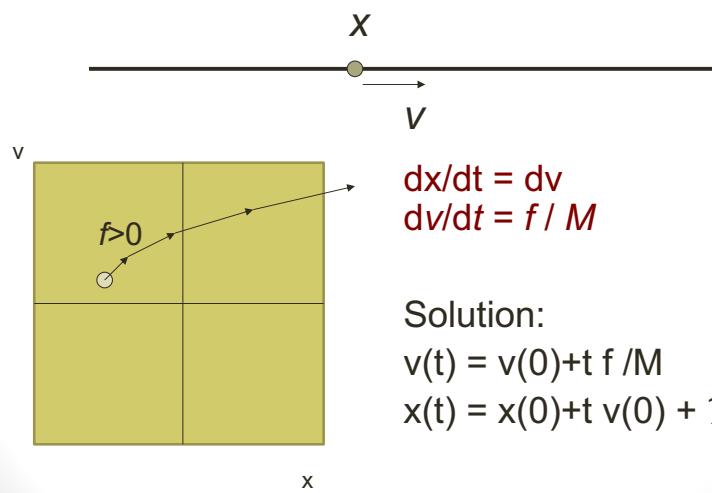
$$\begin{aligned} \dot{x}/dt &= v \\ \dot{v}/dt &= f / M \end{aligned}$$

Solution:

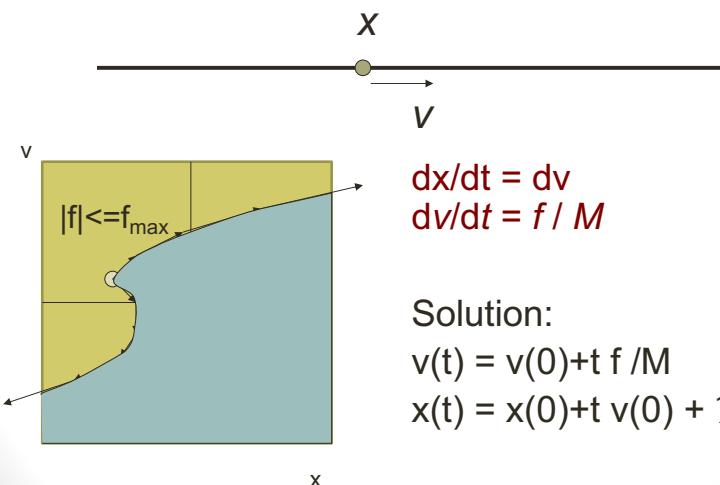
$$v(t) = v(0) + t f / M$$

$$x(t) = x(0) + t v(0) + \frac{1}{2} t^2 f / M$$

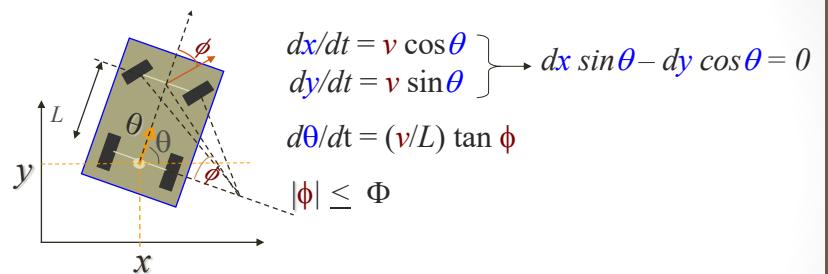
## Example: 1D Point Mass



## Example: 1D Point Mass



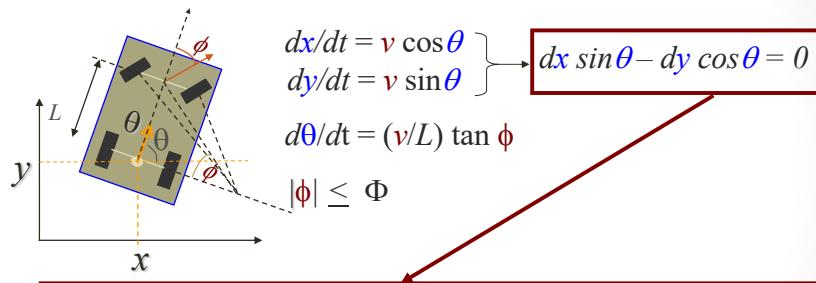
## Example: Car-Like Robot



Configuration space is 3-dimensional:  $q = (x, y, \theta)$

But control space is 2-dimensional:  $(v, \phi)$  with  
 $|v| = \sqrt{(dx/dt)^2 + (dy/dt)^2}$

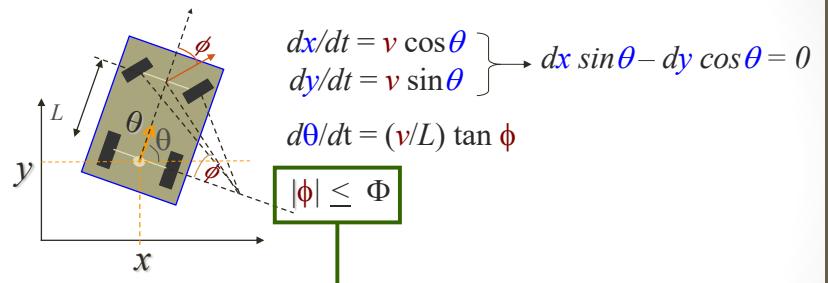
## Example: Car-Like Robot



$q = (x, y, \theta)$   
 $q' = dq/dt = (dx/dt, dy/dt, d\theta/dt)$   
 $dx \sin \theta - dy \cos \theta = 0$  is a particular form of  $f(q, q') = 0$

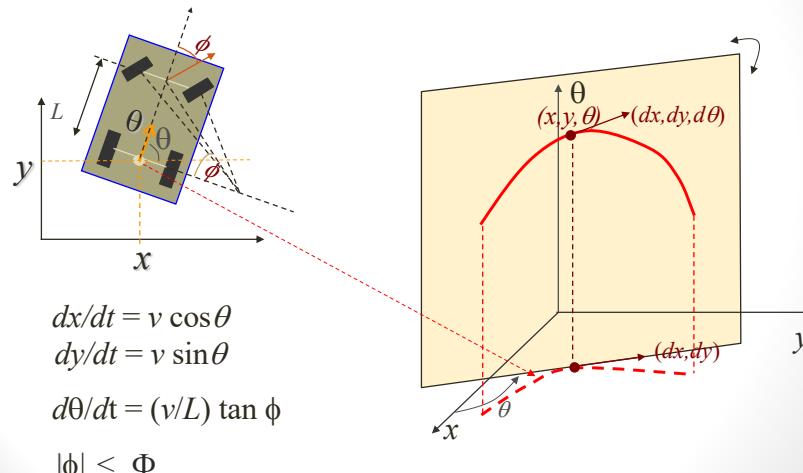
A robot is **nonholonomic** if its motion is constrained by a non-integrable equation of the form  $f(q, q') = 0$

## Example: Car-Like Robot

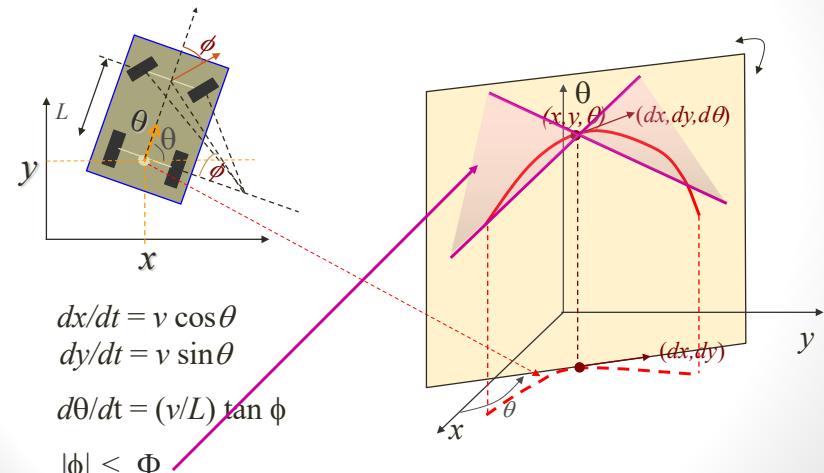


Lower-bounded turning radius

## How Can This Work? Tangent Space/Velocity Space



## How Can This Work? Tangent Space/Velocity Space



## Nonholonomic Path Planning Approaches

- Two-phase planning (path deformation):
  - Compute collision-free path ignoring nonholonomic constraints
  - Transform this path into a nonholonomic one
  - Efficient, but possible only if robot is “controllable”
  - Need for a “good” set of maneuvers
- Direct planning (control-based sampling):
  - Use “control-based” sampling to generate a tree of milestones until one is close enough to the goal (deterministic or randomized)
  - Robot need not be controllable
  - Applicable to high-dimensional c-spaces

## Control-Based Sampling

- PRM sampling technique: Pick each milestone in some region
- **Control-based sampling:**
  1. Pick control vector (at random or not)
  2. Integrate equation of motion over short duration (picked at random or not)
  3. If the motion is collision-free, then the endpoint is the new milestone

→ Tree-structured roadmaps  
 → Need for **endgame** regions

## Example

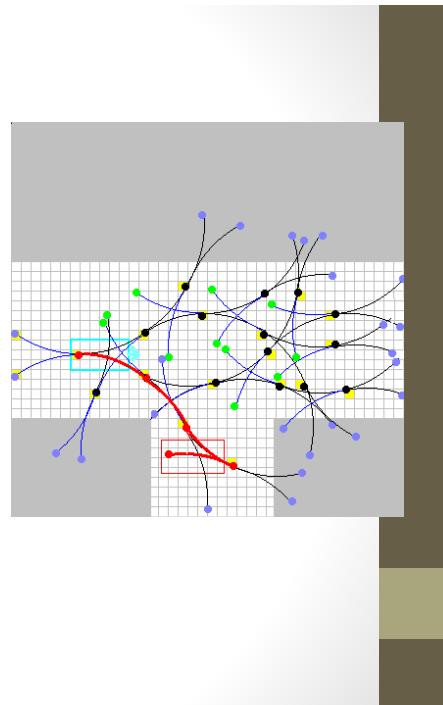
$$dx/dt = v \cos \theta$$

$$dy/dt = v \sin \theta$$

$$d\theta/dt = (v/L) \tan \phi$$

$$|\phi| \leq \Phi$$

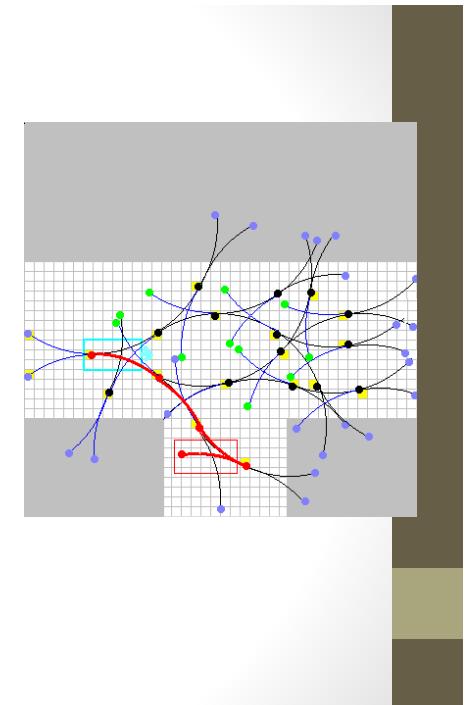
1. Select a milestone  $m$
2. Pick  $v$ ,  $\phi$ , and  $\delta t$
3. Integrate motion from  $m$   
→ new milestone  $m'$



## Example

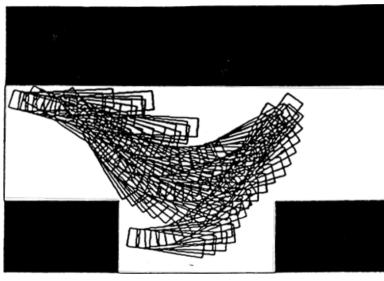
**Indexing array:**

A 3-D grid is placed over the configuration space. Each milestone falls into one cell of the grid. A maximum number of milestones is allowed in each cell (e.g., 2 or 3).



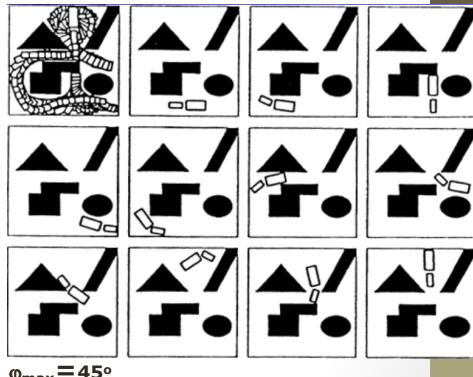
## Computed Paths

Car That Can Only Turn Left



$\varphi_{\max} = 45^\circ, \varphi_{\min} = 22.5^\circ$

Tractor-trailer



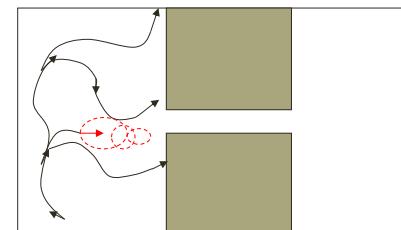
## Control-Sampling RRT

- Configuration generator  $f(x, u)$
- Build a tree  $T$  of configurations
- Extend:
  - Sample a configuration  $x_{\text{rand}}$  from  $X$  at random
  - Find the node  $x_{\text{near}}$  in  $T$  that is closest to  $x_{\text{rand}}$
  - Pick a control  $u$  that brings  $f(x_{\text{near}}, u)$  close to  $x_{\text{rand}}$
  - Add  $f(x_{\text{near}}, u)$  as a child of  $x_{\text{near}}$  in  $T$



## Weaknesses of RRT's strategy

- Depends on the domain from which  $x_{rand}$  is sampled
- Depends on the notion of “closest”
- A tree that is grown “badly” by accident can greatly slow convergence



## Other strategies

- Dynamic-domain RRTs (Yershova et al 2008)
- Perturb samples in a neighborhood (EST, SBL)
- Lazy planning: delay expensive collision checks until end