### **Robotic Motion Planning: Bug Algorithms**

(with some discussion on curve tracing and sensors)

Robotics Institute 16-735 http://voronoi.sbp.ri.cmu.edu/~motion

Howie Choset http://voronoi.sbp.ri.cmu.edu/~choset

### What's Special About Bugs

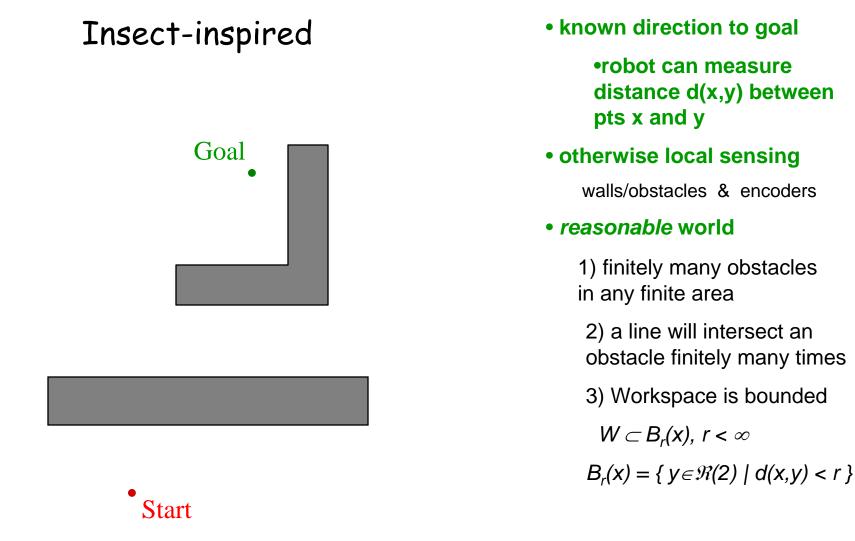
- Many planning algorithms assume global knowledge
- Bug algorithms assume only *local* knowledge of the environment and a global goal
- Bug behaviors are simple:
  - 1) Follow a wall (right or left)
  - 2) Move in a straight line toward goal
- Bug 1 and Bug 2 assume essentially tactile sensing
- Tangent Bug deals with finite distance sensing

### A Few General Concepts

- Workspace W
  - $\Re(2)$  or  $\Re(3)$  depending on the robot
  - could be infinite (open) or bounded (closed/compact)
- Obstacle *WO*<sub>i</sub>
- Free workspace  $W_{free} = W \setminus \bigcup_{i} WO_{i}$

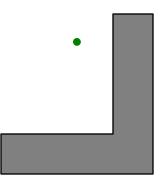
### The Bug Algorithms

provable results...



### **Buginner Strategy**

#### "Bug O" algorithm



#### known direction to goal

#### • otherwise local sensing

walls/obstacles & encoders

Some notation:

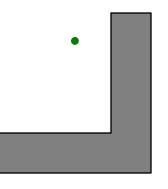
 $q_{start}$  and  $q_{goal}$ 

"hit point" q<sup>H</sup>i "leave point q<sup>L</sup>i

A *path* is a sequence of hit/leave pairs bounded by  $q_{start}$  and  $q_{goal}$ 

### **Buginner Strategy**

#### "Bug O" algorithm





• otherwise local sensing

walls/obstacles & encoders

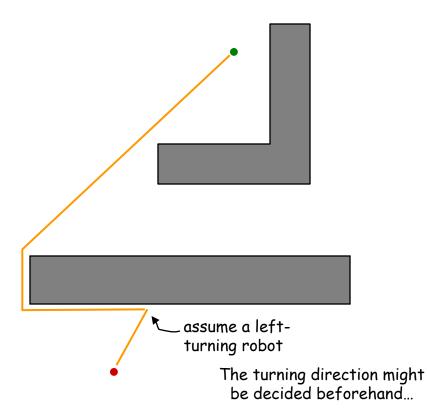
1) head toward goal

2) follow obstacles until you can head toward the goal again

3) continue

### **Buginner Strategy**

#### "Bug O" algorithm



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### Bug Zapper

#### What map will foil Bug 0?

#### "Bug O" algorithm

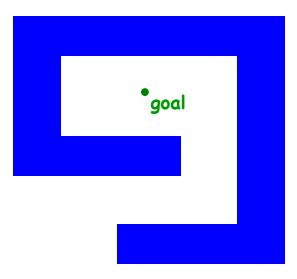
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### Bug Zapper

#### What map will foil Bug 0?



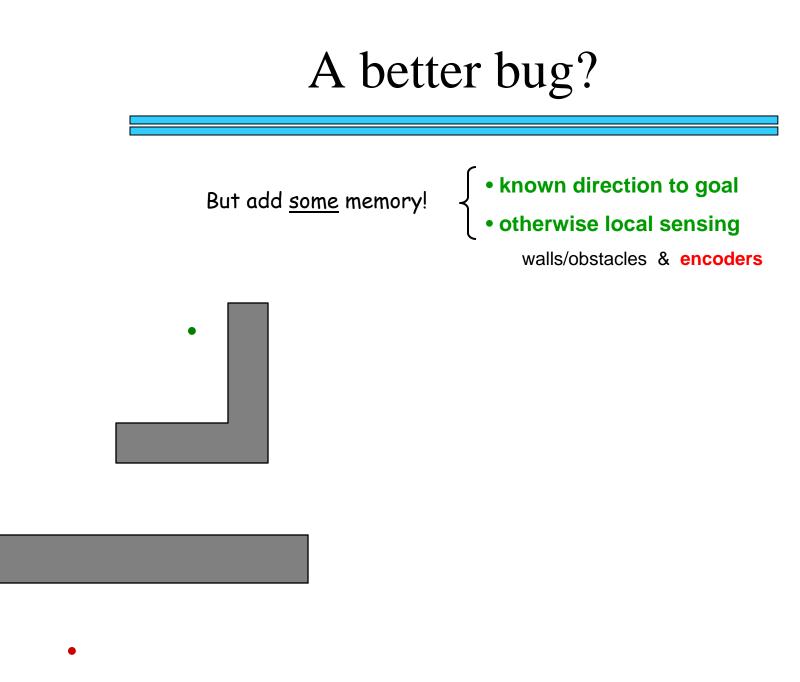
#### "Bug O" algorithm

1) head toward goal

2) follow obstacles until you can head toward the goal again

3) continue

• start



16-735, Howie Choset with slides from G.D. Hager and Z. Dodds

improvement ideas?



## Bug 1

But <u>some</u> computing power!

- known direction to goal
  otherwise local sensing

walls/obstacles & encoders

#### "Bug 1" algorithm

1) head toward goal

2) if an obstacle is encountered, circumnavigate it and remember how close you get to the goal

3) return to that closest point (by wall-following) and continue

Vladimir Lumelsky & Alexander Stepanov: Algorithmica 1987



## Bug 1

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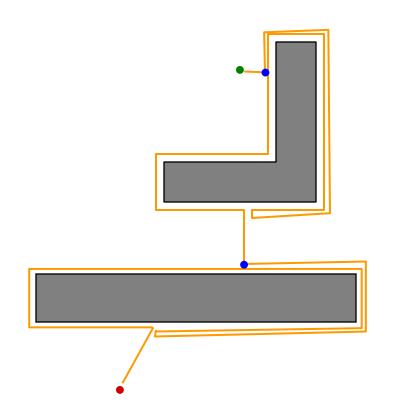
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Vladimir Lumelsky & Alexander Stepanov: Algorithmica 1987 16-735, Howie Choset with slides from G.D. Hager and Z. Dodds



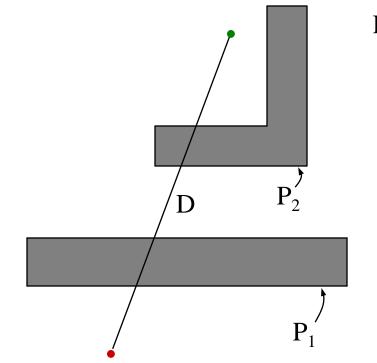
### BUG 1 More formally

- Let  $q_{0}^{L} = q_{start}$ ; i = 1
- repeat
  - repeat
    - from  $q_{i-1}^L$  move toward  $q_{goal}$
  - until goal is reached or obstacle encountered at q<sup>H</sup><sub>i</sub>
  - if goal is reached, exit
  - repeat
    - follow boundary recording pt  $q_i^L$  with shortest distance to goal
  - until  $q_{goal}$  is reached or  $q_{i}^{H}$  is re-encountered
  - if goal is reached, exit
  - Go to  $q_{i}^{L}$
  - if move toward  $q_{goal}$  moves into obstacle
    - exit with failure
  - else
    - i=i+1
    - continue



## Bug 1 analysis

Bug 1: Path Bounds



What are upper/lower bounds on the path length that the robot takes?

- D = straight-line distance from start to goal
- $P_i$  = perimeter of the *i* th obstacle

#### Lower bound:

What's the shortest distance it might travel?

#### Upper bound:

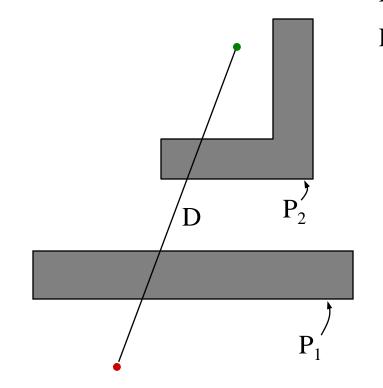
What's the longest distance it might travel?

What is an environment where your upper bound is required?



## Bug 1 analysis

Bug 1: Path Bounds



What are upper/lower bounds on the path length that the robot takes?

- D = straight-line distance from start to goal
- $P_i$  = perimeter of the *i* th obstacle

Lower bound: What's the shortest distance it might travel?

D

Upper bound: What's the longest distance it might travel?

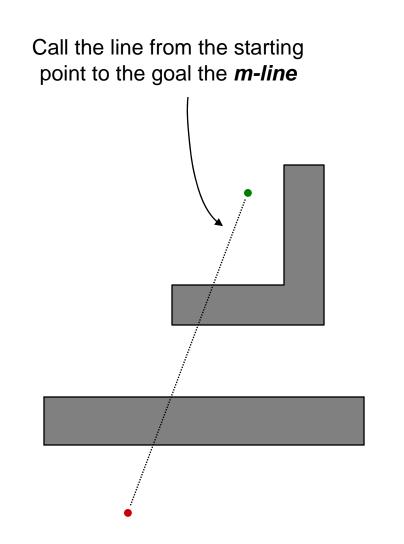
 $D + 1.5 \Sigma P_{i}$ 

What is an environment where your upper bound is required? 16-735, Howie Choset with slides from G.D. Hager and Z. Dodds

### How Can We Show Completeness?

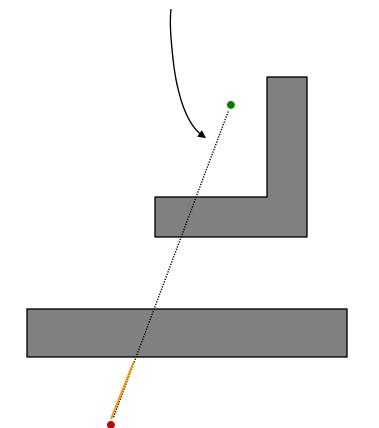
- An algorithm is *complete* if, in finite time, it finds a path if such a path exists or terminates with failure if it does not.
- Suppose BUG1 were incomplete
  - Therefore, there is a path from start to goal
    - By assumption, it is finite length, and intersects obstacles a finite number of times.
  - BUG1 does not find it
    - Either it terminates incorrectly, or, it spends an infinite amount of time
    - Suppose it never terminates
      - but each leave point is closer to the obstacle than corresponding hit point
      - Each hit point is closer than the last leave point
      - Thus, there are a finite number of hit/leave pairs; after exhausting them, the robot will proceed to the goal and terminate
    - Suppose it terminates (incorrectly)
    - Then, the closest point after a hit must be a leave where it would have to move into the obstacle
      - But, then line from robot to goal must intersect object even number of times (Jordan curve theorem)
      - But then there is another intersection point on the boundary closer to object. Since we
        assumed there is a path, we must have crossed this pt on boundary which contradicts the
        definition of a leave point.

### Another step forward?



#### "Bug 2" Algorithm

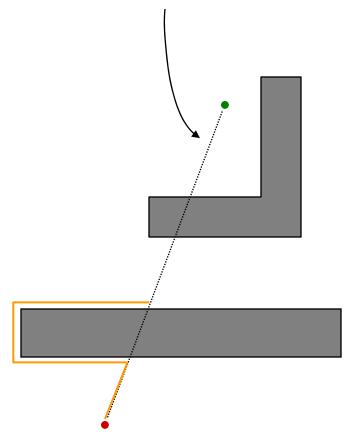
Call the line from the starting point to the goal the *m-line* 



### "Bug 2" Algorithm

1) head toward goal on the *m*-line

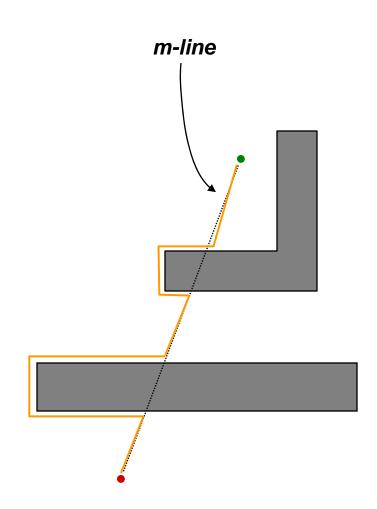
Call the line from the starting point to the goal the *m-line* 



#### "Bug 2" Algorithm

1) head toward goal on the *m*-line

2) if an obstacle is in the way, follow it until you encounter the m-line again.

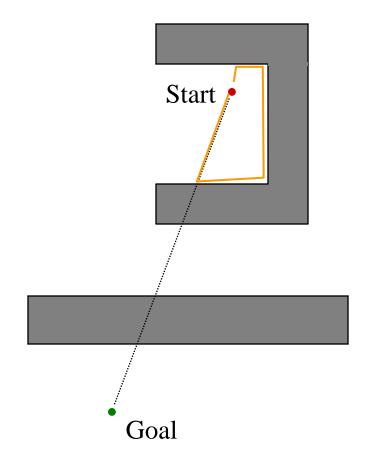


#### "Bug 2" Algorithm

1) head toward goal on the *m*-line

2) if an obstacle is in the way, follow it until you encounter the m-line again.

3) Leave the obstacle and continue toward the goal



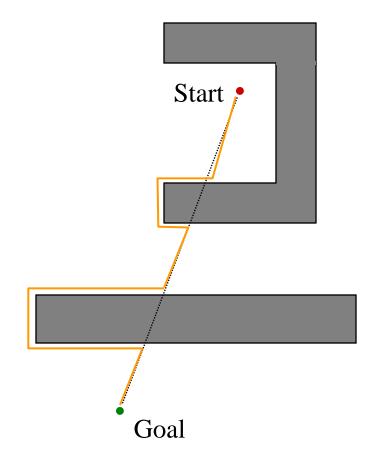
#### "Bug 2" Algorithm

1) head toward goal on the *m*-line

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3) Leave the obstacle and continue toward the goal

16-735, Howie Choset with slides from G.D. Hager and Z. Dodds NO! How do we fix this?



#### "Bug 2" Algorithm

1) head toward goal on the *m*-line

2) if an obstacle is in the way, follow it until you encounter the m-line again *closer to the goal*.

3) Leave the obstacle and continue toward the goal

#### Better or worse than Bug1?

### BUG 2 More formally

- Let  $q_{0}^{L} = q_{start}$ ; i = 1
- repeat
  - repeat
    - from  $q_{i-1}^L$  move toward  $q_{goal}$  along the m-line
  - until goal is reached or obstacle encountered at q<sup>H</sup><sub>i</sub>
  - if goal is reached, exit
  - repeat
    - follow boundary
  - until  $q_{goal}$  is reached or  $q_i^H$  is re-encountered or m-line is re-encountered, x is not  $q_i^H$ ,  $d(x,q_{goal}) < d(q_i^H,q_{goal})$  and way to goal is unimpeded
  - if goal is reached, exit
  - if  $q_{i}^{H}$  is reached, return failure
  - else
    - $q_i^L = m$
    - i=i+1
    - continue

# head-to-head comparison

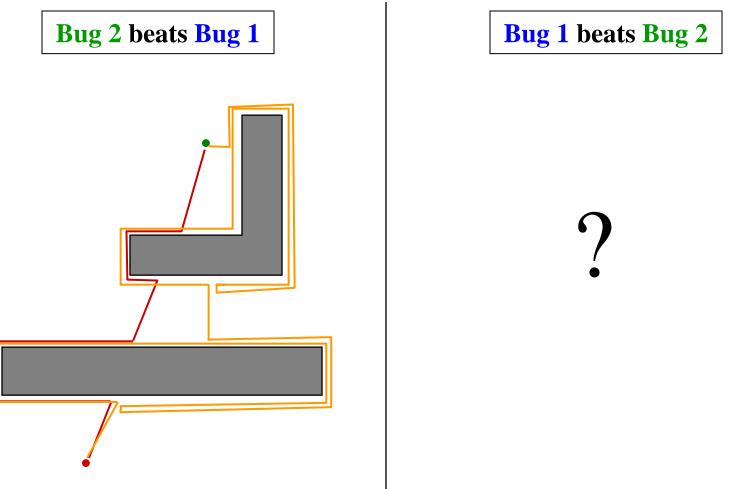
Draw worlds in which Bug 2 does better than Bug 1 (and vice versa).

Bug 2 beats Bug 1

**Bug 1** beats Bug 2

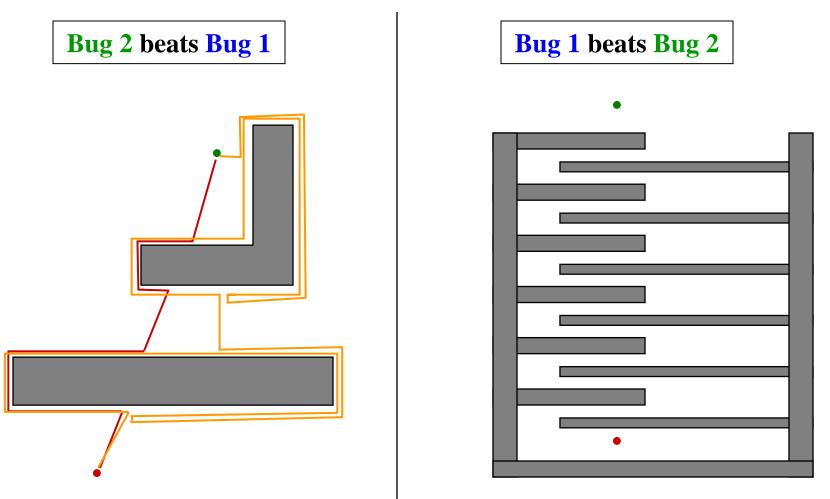
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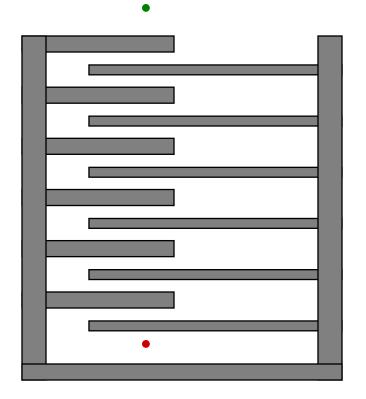
### BUG 1 vs. BUG 2

- BUG 1 is an *exhaustive search algorithm* 
  - it looks at all choices before commiting
- BUG 2 is a *greedy* algorithm
  - it takes the first thing that looks better
- In many cases, BUG 2 will outperform BUG 1, but
- BUG 1 has a more predictable performance overall



## Bug 2 analysis

#### Bug 2: Path Bounds



What are upper/lower bounds on the path length that the robot takes?

- D = straight-line distance from start to goal
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#### Lower bound:

What's the shortest distance it might travel?

D

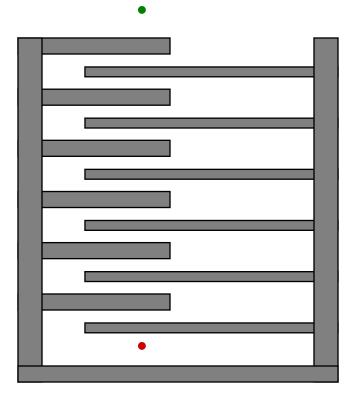
Upper bound: What's the longest distance it might travel?

What is an environment where your upper bound is required?



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Lower bound:

What's the shortest distance it might travel? D

Upper bound: What's the longest distance it might travel?

 $\mathbf{D} + \sum_{i} \frac{\mathbf{n}_{i}}{2} \mathbf{P}_{i}$ 

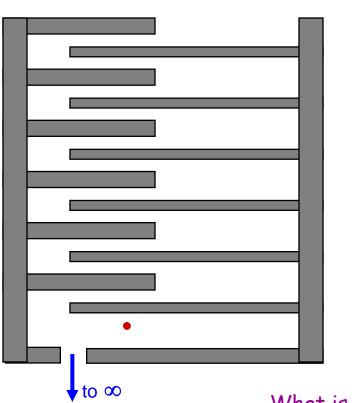
 $\mathbf{n}_i = \#$  of s-line intersections of the *i* th obstacle

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Bug 2: Path Bounds



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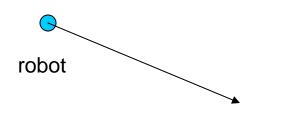
What is an environment where your upper bound is required?

### A More Realistic Bug

- As presented: global beacons plus contact-based wall following
- The reality: we typically use some sort of range sensing device that lets us look ahead (but has finite resolution and is noisy).
- Let us assume we have a range sensor
- distance fn:  $\rho(\mathbf{x}, \theta) = \min_{\lambda \ge 0} d(\mathbf{x}, \mathbf{x} + \lambda[\mathbf{c}_{\theta}, \mathbf{s}_{\theta}])$ s.t.  $\mathbf{x} + \lambda[\mathbf{c}_{\theta}, \mathbf{s}_{\theta}]) \in \bigcup_{i} WO_{i}$
- Note we write  $\rho: \Re(2) \times S(1) \rightarrow \Re$ - what is S(1) ?
- Saturated distance:  $\rho_R(x,\theta) = \rho(x,\theta)$  if  $\rho(x,\theta) < R$ , else  $\infty$

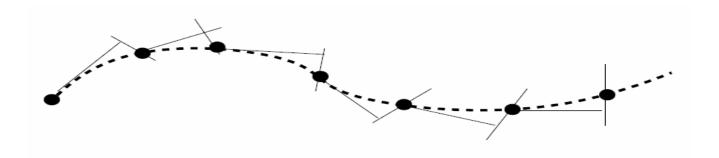
#### Move to Goal

- Distance d(a,b) =  $((a_x b_x)^2 + (a_y b_y)^2)^{\frac{1}{2}}$
- Gradient descent of d(a,b), i.e., decrease distance to the goal



⊖ goal

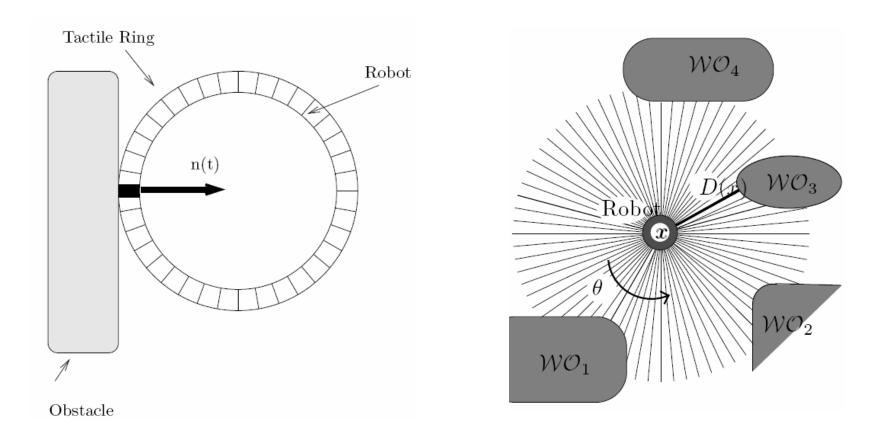
#### Circumnavigating Obstacles: Curve Tracing



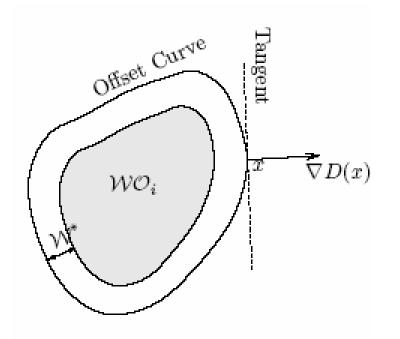
Predict: Tangent

Correct: Something else

#### Normal (and hence Tangent) to Obstacle



#### Circumnavigate Obstacles: Boundary Following



 $D(x) = \min d(x,c)$ 

Normal is parallel to  $\nabla D(x)$ 

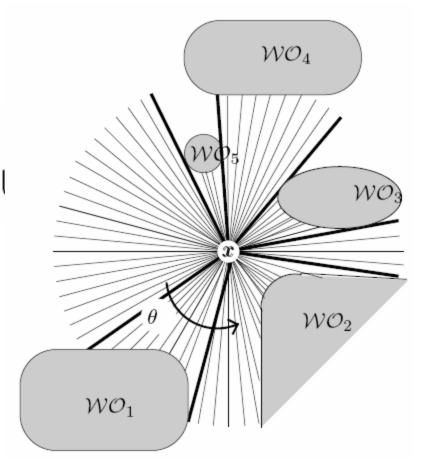
Increase/Decrease/Same

Safety distance W\*

Tangent is orthogonal to both

$$\dot{c}(t) = v \quad v \text{ is in } (n(c(t))^{\perp})$$

#### **Raw Distance Function**



$$\rho(x,\theta) = \min_{\lambda \in [0,\infty]} d(x, x + \lambda [\cos \theta, \sin \theta]^T),$$

such that  $x + \lambda [\cos \theta, \sin \theta]^T \in [$ 

#### Saturated raw distance function

$$\rho_R(x,\theta) = \begin{cases} \rho(x,\theta), & \text{if } \rho(x,\theta) < R\\ \infty, & \text{otherwise.} \end{cases}$$

#### **Implicit Function Theorem**

 $G(x) = D(x) - W^*$ 

Roots of G(x) trace the offset curve

DG(x) = DD(x), which is like a gradient in Euclidean spaces

Null of DG(x) is tangent, hence perp of DD(x) is too

THEOREM D.1.1 (Implicit Function Theorem) Let  $f : \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^n$  be a smooth vector-valued function, f(x, y). Assume that  $D_y f(x_0, y_0)$  is invertible for some  $x_0 \in \mathbb{R}^m$ ,  $y_0 \in \mathbb{R}^n$ . Then there exist neighborhoods  $X_0$  of  $x_0$  and  $Z_0$  of  $f(x_0, y_0)$ and a unique, smooth map  $g : X_0 \times Z_0 \to \mathbb{R}^n$  such that

f(x,g(x,z))=z

for all  $x \in X_0$ ,  $z \in Z_0$ .

#### Correction

THEOREM D.2.1 (Newton-Raphson Convergence Theorem) Let  $f : \mathbb{R}^n \to \mathbb{R}^n$  and  $f(y^*) = 0$ . For some  $\rho > 0$ , let f satisfy

•  $Df(y^*)$  is nonsingular with bounded inverse, i.e.,  $||(Df(y^*))^{-1}|| \le \beta$ 

$$||Df(x) - Df(y)|| \le \gamma ||x - y|| \text{ for all } x, y \in B_{\rho}(y^*), \text{ where } \gamma \le \frac{2}{\rho \beta}$$

Now consider the sequence  $\{y^h\}$  defined by

$$y^{h+1} = y^h - (Df(y^h))^{-1}f(y^h),$$

for any  $y^0 \in B_{\rho}(y^*)$ . Then  $y^h \in B_{\rho}(y^*)$  for all h > 0, and the sequence  $\{y^h\}$  quadratically converges onto  $y^*$ , i.e.,

 $||y^{h+1} - y^*|| \le a ||y^h - y^*||^2$ where  $a = \frac{\beta \gamma}{2(1 - \rho \beta \gamma)} < \frac{1}{\rho}$ .