# Robotic Motion Planning: Potential Functions

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### The Basic Idea

$$U(q) = U_{\text{att}}(q) + U_{\text{rep}}(q)$$

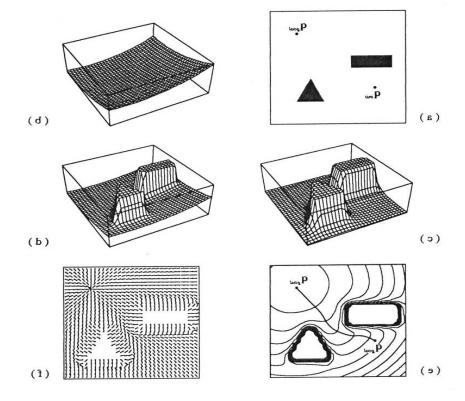
$$\nabla U(q) = DU(q)^T = \left[\frac{\partial U}{\partial q_1}(q), \dots, \frac{\partial U}{\partial q_m}(q)\right]^T$$

#### **Compute Distance**

- Polygon
- Sensor
- Grid

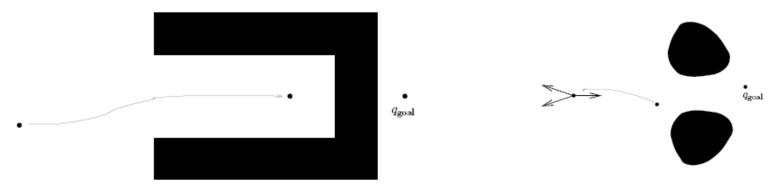
#### **Local Minima**

- Wavefront
- Navigation Function



### Potential Functions Question

How do we know that we have only a single (global) minimum



- We have two choices:
  - not guaranteed to be a global minimum: do something other than gradient descent (what?)
  - make sure only one global minimum (a navigation function, which we'll see later).



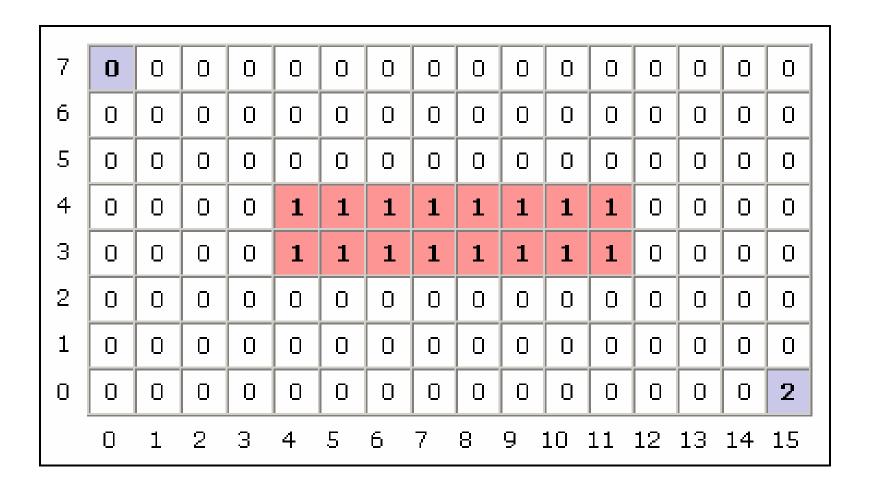
### Solutions??

- Wavefront
- Navigation Functions

#### The Wave-front Planner

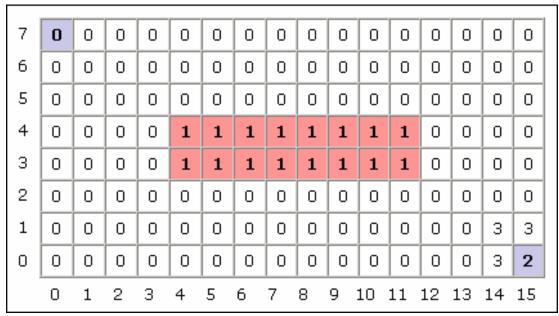
- Apply the brushfire algorithm starting from the goal
- Label the goal pixel 2 and add all zero neighbors to L
  - While  $L \neq \emptyset$ 
    - pop the top element of L, t
    - set d(t) to 1+min<sub>t'  $\in N(t), d(t) > 1$ </sub> d(t')
    - Add all t'∈ N(t) with d(t)=0 to L (at the end)
- The result is now a distance for every cell
  - gradient descent is again a matter of moving to the neighbor with the lowest distance value

### The Wavefront Planner: Setup



### The Wavefront in Action (Part 1)

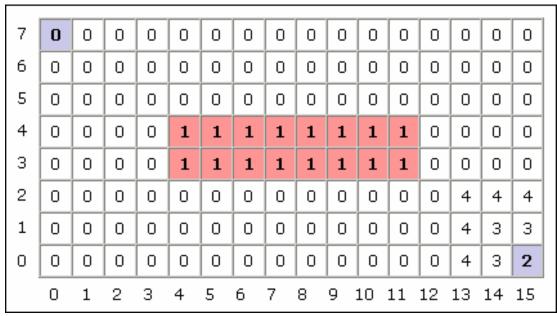
- Starting with the goal, set all adjacent cells with "0" to the current cell + 1
  - 4-Point Connectivity or 8-Point Connectivity?
  - Your Choice. We'll use 8-Point Connectivity in our example



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### The Wavefront in Action (Part 2)

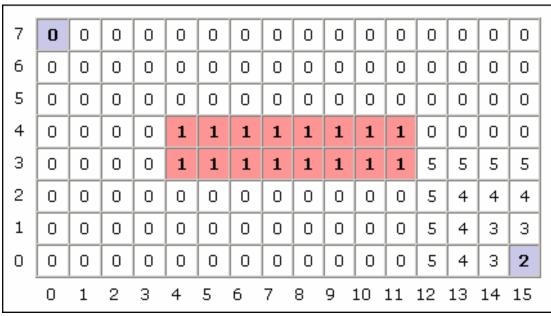
- Now repeat with the modified cells
  - This will be repeated until no 0's are adjacent to cells with values >= 2
    - 0's will only remain when regions are unreachable



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## The Wavefront in Action (Part 3)

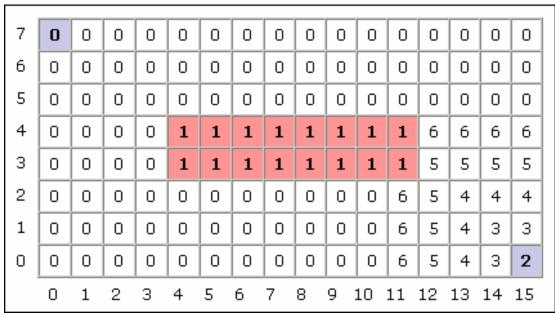
Repeat again...



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## The Wavefront in Action (Part 4)

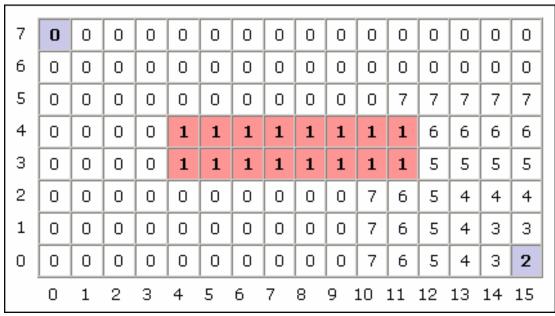
And again...



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### The Wavefront in Action (Part 5)

And again until...



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# The Wavefront in Action (Done)

- You're done
  - Remember, 0's should only remain if unreachable regions exist

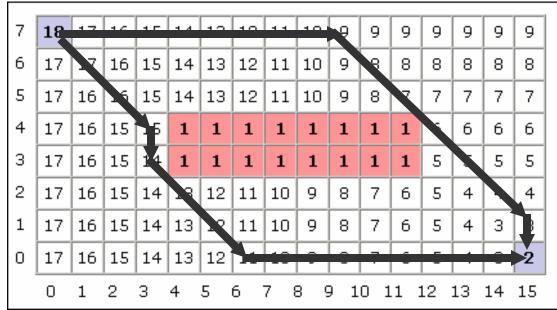
7	18	17	16	15	14	13	12	11	10	9	9	9	9	9	9	9
6	17	17	16	15	14	13	12	11	10	9	8	8	8	8	8	8
5	17	16	16	15	14	13	12	11	10	9	8	7	7	7	7	7
4	17	16	15	15	1	1	1	1	1	1	1	1	6	6	6	6
3	17	16	15	14	1	1	1	1	1	1	1	1	5	5	5	5
2	17	16	15	14	13	12	11	10	9	8	7	6	5	4	4	4
1	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	3
0	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2
	0	1	2	3	4	5	6	7 8	3 9	9 1	0 1	.1 :	12	13	14	15

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### The Wavefront, Now What?

- To find the shortest path, according to your metric, simply always move toward a cell with a lower number
  - The numbers generated by the Wavefront planner are roughly proportional to their distance from the goal

Two
possible
shortest
paths
shown



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### Wavefront (Overview)

- Divide the space into a grid.
- Number the squares starting at the start in either 4 or 8 point connectivity starting at the goal, increasing till you reach the start.
- Your path is defined by any uninterrupted sequence of decreasing numbers that lead to the goal.

### **Navigation Functions**

- A function  $\phi: Q_{free} \rightarrow [0,1]$  is called a *navigation function if it* 
  - is smooth (or at least C<sup>2</sup>)
  - has a unique minimum at q<sub>goal</sub>
  - is uniformly maximal on the boundary of free space
  - is Morse
- A function is Morse if every critical point (a point where the gradient is zero) is isolated.
- The question: when can we construct such a function?

### Sphere World

- Suppose that the world is a sphere of radius r<sub>0</sub> centered at q<sub>0</sub> containing n obstacles of radius r<sub>i</sub> centered at q<sub>i</sub>, i=1 .. n
  - $-\beta_0(q) = -d^2(q,q_0) + r_0^2$
  - $\beta_i(q) = d^2(q,q_i) r_i^2$

$$QO_i = \{ q \mid \beta_i(q) \le 0 \}$$

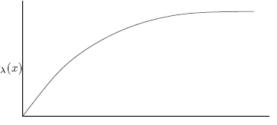
- Define  $\beta(q) = \prod \beta_i(q)$  (Repulsive)
  - note this is zero on any obstacle boundary, positive in free space and negative inside an obstacle
- Define  $\gamma_{\kappa}(q) = (d(q, q_{\text{goal}}))^{2\kappa}$  (Attractive)
  - note this will be zero at the goal, and increasing as we move away
  - κ controls the rate of growth

### Sphere World

- Consider now  $\frac{\gamma_{\kappa}}{\beta}(q)$ 
  - $-\frac{\gamma_{\kappa}}{\beta}(q)$  is only zero at the goal
  - $\frac{\gamma_\kappa}{\beta}(q)$  goes to infinity at the boundary of any obstacle
  - By increasing  $\kappa$ , we can make the gradient at any direction point toward the goal
  - It is possible to show that the only stationary point is the goal, with positive definite Hessian because  $\partial \gamma_{\kappa}/\partial q$  dominates  $\partial \beta/\partial q$ ,
    - therefore no local minima
- In short, following the gradient of  $\frac{\gamma_{\kappa}}{\beta}(q)$  is guaranteed to get to the goal (for a large enough value of  $\kappa$ )

# An Example: Sphere World

- One problem: the value  $\frac{\gamma_{\kappa}}{\beta}(q)(q)$  may be very large
- A solution: introduce a "switch"  $\sigma_{\lambda}(x) = \frac{x}{\lambda + x}$ ,  $\lambda > 0$ .



- Now, define  $s(q, \lambda) = \left(\sigma_{\lambda} \circ \frac{\gamma_{\kappa}}{\beta}\right)(q) = \left(\frac{\gamma_{\kappa}}{\lambda \beta + \gamma_{\kappa}}\right)(q)$ 
  - this bounds the value of the function
  - however,  $s(q, \lambda)$  may turn out not to be Morse
- A solution: introduce a "sharpening function"  $\xi_{\kappa}(x) = x^{\frac{1}{\kappa}}$

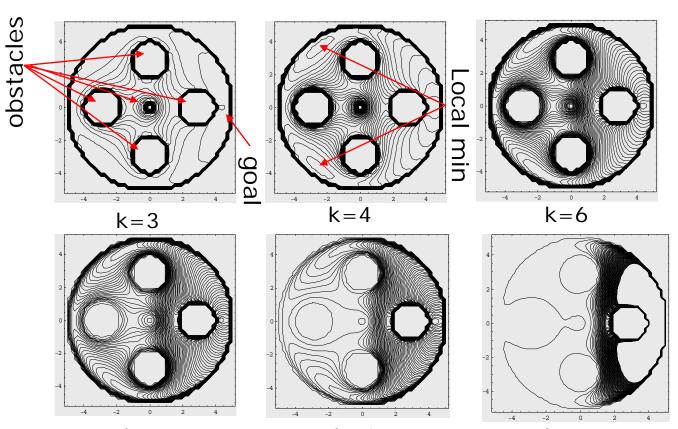
$$\varphi(q) = \left(\xi_{\kappa} \circ \sigma_{1} \circ \frac{\gamma_{\kappa}}{\beta}\right)(q) = \frac{d^{2}(q, q_{\text{goal}})}{\left[\left(d\left(q, q_{\text{goal}}\right)\right)^{2\kappa} + \beta(q)\right]^{1/\kappa}}$$

For large enough  $\kappa$ , this is a navigation function on the sphere world!

# Navigation Function for Sphere World

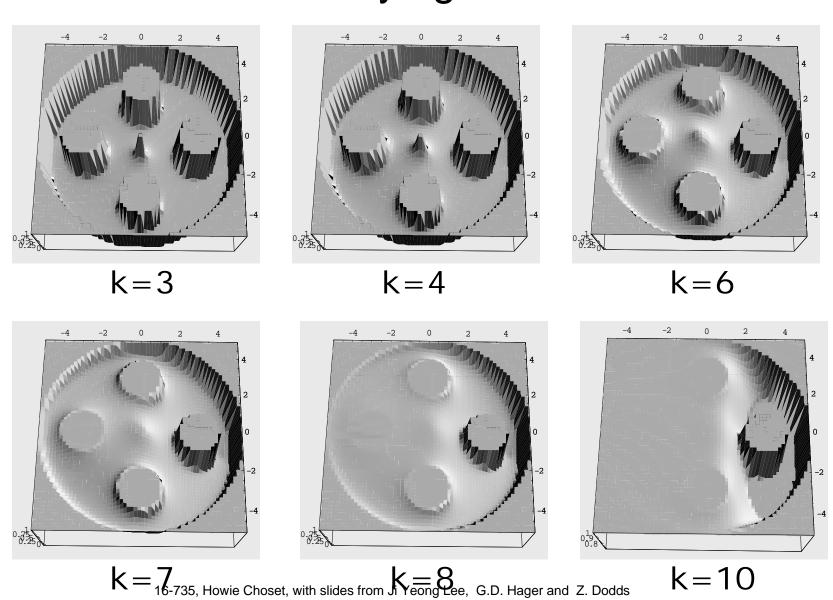
$$\varphi(q) = \left(\xi_{\kappa} \circ \sigma_{1} \circ \frac{\gamma_{\kappa}}{\beta}\right)(q) = \frac{d^{2}(q, q_{\text{goal}})}{\left[\left(d\left(q, q_{\text{goal}}\right)\right)^{2\kappa} + \beta(q)\right]^{1/\kappa}}$$

• For sufficiently large k,  $\varphi(q)$  is a navigation function



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# Navigation Function : $\varphi(q)$ , varying k



# From Spheres to Stars and Beyond

- While it may not seem like it, we have solved a very general problem
- Suppose we have a **diffeomorphism**  $\delta$  from some world W to a sphere world S
  - if  $O''_{\kappa}$  is a navigation function on S then
  - O'''<sub>κ</sub>(q) = O''<sub>κ</sub>(δ(q)) is a navigation function W
    - note we also need to the property of the property

Jacobian is full rank

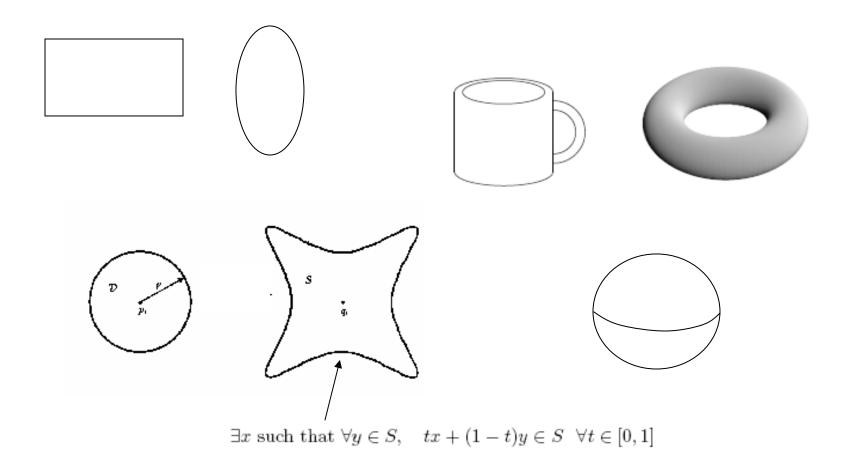
is full rank, the gradient map cannot have new zeros amounted (which could only happen if the gradient was in the null space of the Jacobian)

- A star world is one example where a diffeomorphism is known to exist
  - a star-shaped set is one in which all boundary points can be "seen" from some single point in the space.

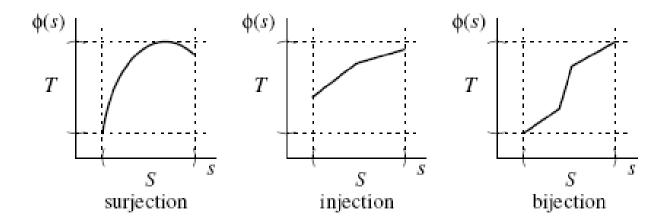


 $\exists x \text{ such that } \forall y \in S, \quad tx + (1-t)y \in S \quad \forall t \in [0,1]$ 

### Which of the following are the same?



# \_\_\_\_jections

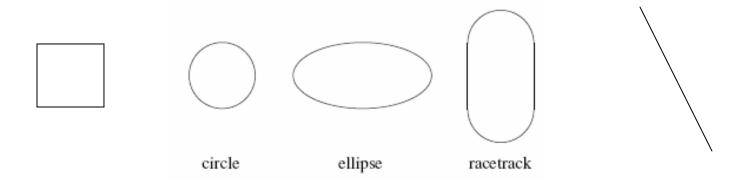


### Diffeomorphism vs. Homeomorphism

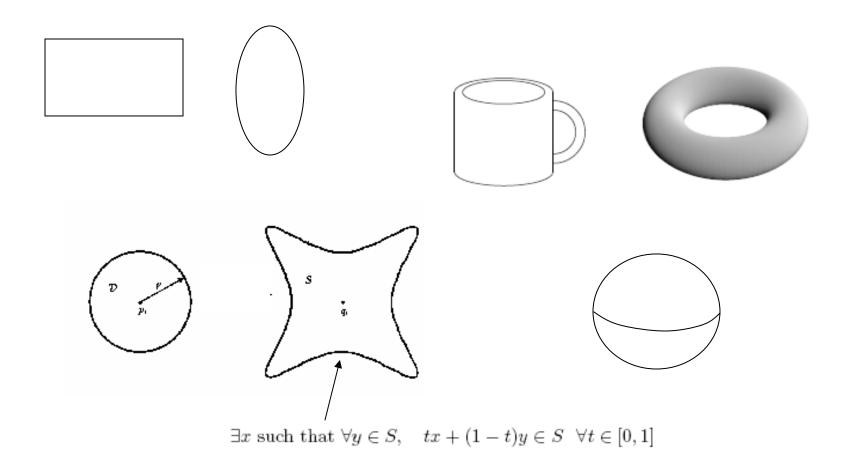
HOMEOMORPHISM If  $\phi: S \to T$  is a bijection, and both  $\phi$  and  $\phi^{-1}$  are continuous, then  $\phi$  is a homeomorphism. When such a  $\phi$  exists, S and T are said to be homeomorphic.

A mapping  $\phi: U \to V$  is said to be *smooth* if all partial derivatives of  $\phi$ , of all orders, are well defined (i.e.,  $\phi$  is of class  $C^{\infty}$ ). With the notion of smoothness, we define a second type of bijection.

DIFFEOMORPHISM A smooth map  $\phi: U \to V$  is a diffeomorphism if  $\phi$  is bijective and  $\phi^{-1}$  is smooth. When such a  $\phi$  exists, U and V are said to be diffeomorphic.



### Which of the following are the same?



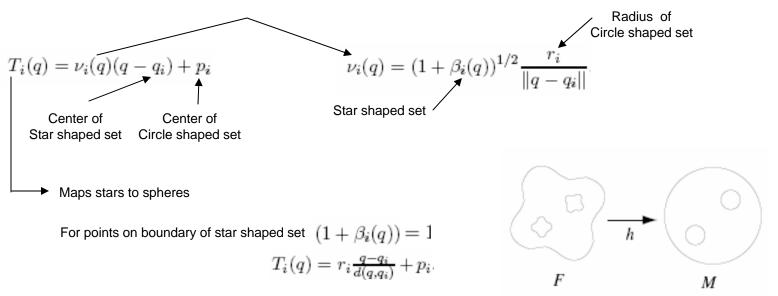
### From Spheres to Stars and Beyond

- While it may not seem like it, we have solved a very general problem
- Suppose we have a **diffeomorphism**  $\delta$  from some world W to a sphere world S
  - if O"<sub>κ</sub> is a navigation function on S then
  - O'''<sub>κ</sub>(q) = O''<sub>κ</sub>(δ(q)) is a navigation function on W!
    - note we also need to take the diffeomorphism into account for distances
    - Because  $\delta$  is a diffeomorphism, the Jacobian is full rank
    - Because the Jacobian is full rank, the gradient map cannot have new zeros introduced (which could only happen if the gradient was in the null space of the Jacobian)
- A star world is one example where a diffeomorphism is known to exist
  - a star-shaped set is one in which all boundary points can be "seen" from some single point in the space.



 $\exists x \text{ such that } \forall y \in S, \quad tx + (1-t)y \in S \quad \forall t \in [0,1]$ 

### Construct the Mapping



For the star-shaped obstacle  $QO_i$ ,

$$s_i(q,\lambda) = \left(\sigma_\lambda \circ \frac{\gamma_\kappa \bar{\beta}_i}{\beta_i}\right)(q) = \left(\frac{\gamma_\kappa \bar{\beta}_i}{\gamma_\kappa \bar{\beta}_i + \lambda \beta_i}\right)(q) \qquad \qquad \bar{\beta}_i = \prod_{j=0, j \neq i}^n \beta_j \qquad \text{Zero on boundary of obstacles except the "current" one} \\ s_{q_{\mathbf{goal}}}(q,\lambda) = 1 - \sum_{i=0}^M s_i \qquad \qquad s_i(q,\lambda) \qquad \text{One on the boundary of $\mathcal{QO}_i$ and Zero on the goal and other obstacle boundaries}$$

 $h_{\lambda}(q)$  is exactly  $T_{i}(q)$  on the boundary of the  $QO_{i}$ 

$$h_{\lambda}(q) = s_{q_{\text{goal}}}(q, \lambda) T_{q_{\text{goal}}}(q) + \sum_{i=1}^{M} s_{i}(q, \lambda) T_{i}(q) \qquad T_{q_{\text{goal}}}(q) = q$$

for a suitable  $\lambda$ ,  $h_{\lambda}(q)$  is smooth, bijective, and has a smooth inverse.

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# Potential Fields on Non-Euclidean Spaces

- Thus far, we've dealt with points in R<sup>n</sup> --- what about real manipulators
- Recall we can think of the gradient vectors as forces -- the basic idea is to define forces in the workspace (which is  $\Re^2$  or  $\Re^3$ )

force f acting at a point  $x = \phi(q)$ 

force u acting in the robot's configuration

$$\dot{x} = J\dot{q}$$
, where  $J = \partial \phi/\partial q$ 

 $u^T \dot{q}$  Power in configuration space

 $f^T\dot{x}$  Power in work space

#### Power is conserved!

$$f^{T}J\dot{q} = u^{T}\dot{q}$$

$$f^{T}J = u^{T}$$

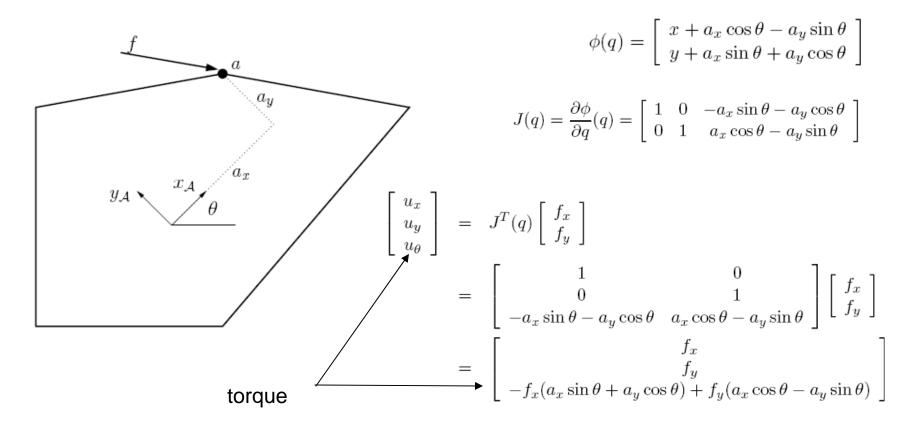
$$J^{T}f = u.$$

### Force on an Object

$$q = [x, y, \theta]^T$$

$$[a_x, a_y]^T$$

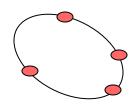
robot's local coordinate frame.



### Potential Function on Rigid Body

pick control points  $\{r_i\}$  on the robot

Pick enough points to "pin down" robot (2 in plane)



$$U_{\text{att},j}(q) = \begin{cases} \frac{1}{2} \zeta_i d^2(r_j(q), r_j(q_{\text{goal}})), & d(r_j(q), r_j(q_{\text{goal}})) \leq d_0 \\ \\ d\zeta_i d(r_i(q), r_i(q_{\text{goal}})) - \frac{1}{2} \zeta_i d^2, & d(r_i(q), r_i(q_{\text{goal}})) > d_0. \end{cases} \qquad \nabla U_{\text{att},j}((q) = \begin{cases} \zeta_i(r_j(q) - r_j(q_{\text{goal}})), & d(r_i(q), r_i(q_{\text{goal}})) \leq d_0, \\ \\ \frac{d\zeta_j(r_j(q) - r_j(q_{\text{goal}}))}{d(r_j(q), r_j(q_{\text{goal}}))}, & d(r_j(q), r_j(q_{\text{goal}})) > d_0. \end{cases}$$

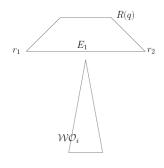
$$\nabla U_{\text{att},j}((q) = \begin{cases} \zeta_i(r_j(q) - r_j(q_{\text{goal}})), & d(r_i(q), r_i(q_{\text{goal}})) \le d_0, \\ \frac{d\zeta_j(r_j(q) - r_j(q_{\text{goal}}))}{d(r_j(q), r_j(q_{\text{goal}}))}, & d(r_j(q), r_j(q_{\text{goal}})) > d_0, \end{cases}$$

$$U_{\text{rep}i,j}(q) = \begin{cases} \frac{1}{2} \eta_j \left( \frac{1}{d_i(r_j(q))} - \frac{1}{Q_i^*} \right)^2, & d_i(r_j(q)) \leq Q_i^* \\ 0, & d_i(r_j(q)) > Q_i^* \end{cases} \qquad \forall U_{\text{rep}i,j}(q) = \begin{cases} \eta_j \left( \frac{1}{Q_i^*} - \frac{1}{d_i(r_j(q))} \right) \frac{1}{d_i^2(r_j(q))} \nabla d_i(r_j(q)), & d_i(r_j(q)) \leq Q_i^*, \\ 0, & d_i(r_j(q)) > Q_i^*. \end{cases}$$

$$\nabla U_{\text{rep}i,j}(q) = \begin{cases} \eta_j \left( \frac{1}{Q_i^*} - \frac{1}{d_i(r_j(q))} \right) \frac{1}{d_i^2(r_j(q))} \nabla d_i(r_j(q)), & d_i(r_j(q)) \leq Q_i^*, \\ 0, & d_i(r_j(q)) > Q_i^*. \end{cases}$$

i & j should switched?

$$\begin{split} u(q) &= \sum_i u_{\mathrm{att}i}(q) + \sum_j u_{\mathrm{rep}j}(q) \\ &= \sum_i J_i^T(q) f_{\mathrm{att}i}(q) + \sum_j J_j^T(q) f_{\mathrm{rep}j}(q) \end{split}$$

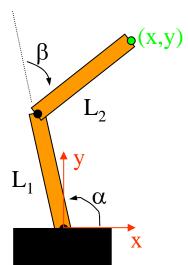


More points please

### Potential Fields for Multiple Bodies

- Recall we can think of the gradient vectors as forces -- the basic idea is to define forces in the workspace (which is  $\Re^2$  or  $\Re^3$ )
  - We have  $J^t f = u$  where f is in W and u is in Q
  - Thus, we can define forces in W and then map them to Q
  - Example: our two-link manipulator

$$\begin{pmatrix} \mathbf{x} \\ \mathbf{y} \end{pmatrix} = \begin{pmatrix} \mathbf{L}_1 \mathbf{c}_{\alpha} \\ \mathbf{L}_1 \mathbf{s}_{\alpha} \end{pmatrix} + \begin{pmatrix} \mathbf{L}_2 \mathbf{c}_{\alpha+\beta} \\ \mathbf{L}_2 \mathbf{s}_{\alpha+\beta} \end{pmatrix}$$



# Potential Fields on Non-Euclidean Spaces

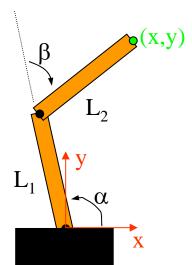
Example: our two-link manipulator

$$- J = -L_1 S_{\alpha} - L_2 S_{\alpha+\beta} - L_2 S_{\alpha+\beta}$$
  
$$L_1 C_{\alpha} + L_2 C_{\alpha+\beta} - L_2 C_{\alpha+\beta}$$

Suppose  $q_{goal} = (0,0)^t$ , then  $f_W = (x,y)$ 

$$f_{q} = x (-L_{1} s_{\alpha} - L_{2} s_{\alpha+\beta}) + y (L_{1} c_{\alpha} + L_{2} c_{\alpha+\beta}) x (-L_{2} s_{\alpha+\beta}) + y L_{2} c_{\alpha+\beta}$$

$$\begin{pmatrix} \mathbf{x} \\ \mathbf{y} \end{pmatrix} = \begin{pmatrix} \mathbf{L}_1 \mathbf{c}_{\alpha} \\ \mathbf{L}_1 \mathbf{s}_{\alpha} \end{pmatrix} + \begin{pmatrix} \mathbf{L}_2 \mathbf{c}_{\alpha+\beta} \\ \mathbf{L}_2 \mathbf{s}_{\alpha+\beta} \end{pmatrix}$$

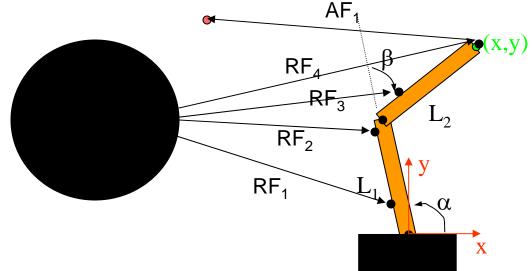


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### In General

- Pick several points on the manipulator
- Compute attractive and repulsive potentials for each
- Transform these into the configuration space and add
- Use the resulting force to move the robot (in its configuration space)

Be careful to use the correct Jacobian!



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## Summary

- Basic potential fields
  - attractive/repulsive forces
- Gradient following and Hessian
- Navigation functions
- Extensions to more complex manipulators