

Potential Field Methods

Acknowledgement: Parts of these course notes are based on notes from courses given by Jean-Claude Latombe at Stanford University (and Chapter 7 in his text *Robot Motion Planning*, Kluwer, 1991), O. Burchan Bayazit at Washington University in St. Louis. Seth Hutchinson at the University of Illinois at Urbana-Champaign, and Leo Joskowicz at Hebrew University.

Potential Field Methods

Basic Idea:

- robot is represented by a point in C-space
 - treat robot like particle under the influence of an **artificial potential field U**
 - U is constructed to reflect (locally) the structure of the free C-space (hence called 'local' methods)
 - originally proposed by Khatib for on-line collision avoidance for a robot with proximity sensors
-

Motion planning is an iterative process

1. compute the artificial force $\vec{F}(\mathbf{q}) = -\nabla U(\mathbf{q})$ at current configuration
 2. take a small step in the direction indicated by this force
 3. repeat until reach goal configuration (or get stuck)
-

Note:

- major problem: local minima (most potential field methods are incomplete)
- advantages: speed
- RPP, a randomized potential field method proposed by Barraquand and Latombe for path planning, can be applied to robots with many dof

The Potential Field (translation only)

Assumption: \mathcal{A} translates freely in $\mathcal{W} = \mathbb{R}^2$ or \mathbb{R}^3 at fixed orientation (so $\mathcal{C} = \mathcal{W}$)

The Potential Function: $\mathbf{U} : \mathcal{C}_{free} \longrightarrow \mathbb{R}^1$

- want robot to be *attracted* to goal and *repelled* from obstacles
 - **attractive potential** $\mathbf{U}_{att}(\mathbf{q})$ associated with \mathbf{q}_{goal}
 - **repulsive potential** $\mathbf{U}_{rep}(\mathbf{q})$ associated with \mathcal{CB}
 - $\mathbf{U}(\mathbf{q}) = \mathbf{U}_{att}(\mathbf{q}) + \mathbf{U}_{rep}(\mathbf{q})$
- $\mathbf{U}(\mathbf{q})$ must be differentiable for every $\mathbf{q} \in \mathcal{C}_{free}$

The Field of Artificial Forces: $\vec{F}(\mathbf{q}) = -\nabla\mathbf{U}(\mathbf{q})$

- $\nabla\mathbf{U}(\mathbf{q})$ denotes gradient of \mathbf{U} at \mathbf{q} , i.e., $\nabla\mathbf{U}(\mathbf{q})$ is a vector that 'points' in the direction of 'fastest change' of \mathbf{U} at configuration \mathbf{q}
- e.g., if $\mathcal{W} = \mathbb{R}^2$, then $\mathbf{q} = (x, y)$ and

$$\nabla\mathbf{U}(\mathbf{q}) = \begin{bmatrix} \frac{\partial\mathbf{U}}{\partial x} \\ \frac{\partial\mathbf{U}}{\partial y} \end{bmatrix}$$

- $|\nabla\mathbf{U}(\mathbf{q})| = \sqrt{\left(\frac{\partial\mathbf{U}}{\partial x}\right)^2 + \left(\frac{\partial\mathbf{U}}{\partial y}\right)^2}$ is the magnitude of the rate of change
- $\vec{F}(\mathbf{q}) = -\nabla\mathbf{U}_{att}(\mathbf{q}) - \nabla\mathbf{U}_{rep}(\mathbf{q})$

The Attractive Potential

Basic Idea: $U_{att}(\mathbf{q})$ should **increase** as \mathbf{q} moves **away from** \mathbf{q}_{goal} (like potential energy increases as you move away from earth's surface)

Naive Idea: $U_{att}(\mathbf{q})$ is linear function of distance from \mathbf{q} to \mathbf{q}_{goal}

- $U_{att}(\mathbf{q})$ does increase as move away from \mathbf{q}_{goal}
- but $-\nabla U_{att}$ has constant magnitude so it doesn't help us get to the goal

Better Idea: $U_{att}(\mathbf{q})$ is a 'parabolic well'

- $U_{att}(\mathbf{q}) = \frac{1}{2}\xi\rho_{goal}^2(\mathbf{q})$, where
 - $\rho_{goal}(\mathbf{q}) = \|\mathbf{q} - \mathbf{q}_{goal}\|$, i.e., Euclidean distance
 - ξ is some positive constant scaling factor
- unique minimum at \mathbf{q}_{goal} , i.e., $U_{att}(\mathbf{q}_{goal}) = 0$
- $U_{att}(\mathbf{q})$ differentiable for all \mathbf{q}

$$\begin{aligned}
 \vec{F}_{att}(\mathbf{q}) = -\nabla U_{att}(\mathbf{q}) &= -\nabla \frac{1}{2}\xi\rho_{goal}^2(\mathbf{q}) \\
 &= -\frac{1}{2}\xi\nabla\rho_{goal}^2(\mathbf{q}) \\
 &= -\frac{1}{2}\xi(2\rho_{goal}(\mathbf{q}))\nabla\rho_{goal}(\mathbf{q})
 \end{aligned}$$

The Gradient $\nabla \rho_{goal}(\mathbf{q})$

Recall: $\rho_{goal}(\mathbf{q}) = \|\mathbf{q} - \mathbf{q}_{goal}\| = (\sum_i (x_i - x_{g_i})^2)^{1/2}$,
 where $\mathbf{q} = (x_1, \dots, x_n)$ and $\mathbf{q}_{goal} = (x_{g_1}, \dots, x_{g_n})$

$$\begin{aligned}
 \nabla \rho_{goal}(\mathbf{q}) &= \nabla \left(\sum_i (x_i - x_{g_i})^2 \right)^{1/2} \\
 &= \frac{1}{2} \left(\sum_i (x_i - x_{g_i})^2 \right)^{-1/2} \nabla \left(\sum_i (x_i - x_{g_i})^2 \right) \\
 &= \frac{1}{2} \left(\sum_i (x_i - x_{g_i})^2 \right)^{-1/2} (2(x_1 - x_{g_1}), \dots, 2(x_n - x_{g_n})) \\
 &= \frac{(x_1, \dots, x_n) - (x_{g_1}, \dots, x_{g_n})}{(\sum_i (x_i - x_{g_i})^2)^{1/2}} \\
 &= \frac{\mathbf{q} - \mathbf{q}_{goal}}{\|\mathbf{q} - \mathbf{q}_{goal}\|} = \frac{\mathbf{q} - \mathbf{q}_{goal}}{\rho_{goal}(\mathbf{q})}
 \end{aligned}$$

So, $-\nabla \rho_{goal}(\mathbf{q})$ is a unit vector directed toward \mathbf{q}_{goal} from \mathbf{q}

Thus, since $-\nabla \mathbf{U}_{att}(\mathbf{q}) = -\frac{1}{2}\xi(2\rho_{goal}(\mathbf{q}))\nabla \rho_{goal}(\mathbf{q})$, we get:

$$\vec{F}_{att}(\mathbf{q}) = -\nabla \mathbf{U}_{att}(\mathbf{q}) = -\xi(\mathbf{q} - \mathbf{q}_{goal})$$

- $\vec{F}_{att}(\mathbf{q})$ is a vector directed toward \mathbf{q}_{goal} with magnitude linearly related to the distance from \mathbf{q} to \mathbf{q}_{goal}
- $\vec{F}_{att}(\mathbf{q})$ converges linearly to zero as \mathbf{q} approaches \mathbf{q}_{goal} – good for stability
- $\vec{F}_{att}(\mathbf{q})$ grows without bound as \mathbf{q} moves away from \mathbf{q}_{goal} – not so good

Conic Well Attractive Potential

Idea: Use a 'conic well' to keep $\vec{F}_{att}(\mathbf{q})$ bounded

- $\mathbf{U}_{att}(\mathbf{q}) = \xi \rho_{goal}(\mathbf{q})$
- $\vec{F}_{att}(\mathbf{q}) = -\nabla \mathbf{U}_{att}(\mathbf{q}) = -\xi \frac{(\mathbf{q} - \mathbf{q}_{goal})}{\|\mathbf{q} - \mathbf{q}_{goal}\|}$
- $\vec{F}_{att}(\mathbf{q})$ is a unit vector (constant magnitude) directed towards \mathbf{q}_{goal} everywhere except $\mathbf{q} = \mathbf{q}_{goal}$
- \mathbf{U}_{att} is singular at the goal – not stable (might cause oscillations)

Better (?) Idea: A hybrid method with parabolic and conic wells

$$\mathbf{U}_{att}(\mathbf{q}) = \begin{cases} \frac{1}{2}\xi \rho_{goal}^2(\mathbf{q}) & \text{if } \rho_{goal}(\mathbf{q}) \leq d \\ d\xi \rho_{goal}(\mathbf{q}) & \text{if } \rho_{goal}(\mathbf{q}) > d \end{cases}$$

and

$$\vec{F}_{att}(\mathbf{q}) = \begin{cases} -\xi(\mathbf{q} - \mathbf{q}_{goal}) & \text{if } \|\mathbf{q} - \mathbf{q}_{goal}\| \leq d \\ -d\xi \frac{(\mathbf{q} - \mathbf{q}_{goal})}{\|\mathbf{q} - \mathbf{q}_{goal}\|} & \text{if } \|\mathbf{q} - \mathbf{q}_{goal}\| > d \end{cases}$$

The Repulsive Potential

Basic Idea: \mathcal{A} should be repelled from obstacles

- never want to let \mathcal{A} 'hit' an obstacle
- if \mathcal{A} is far from obstacle, don't want obstacle to affect \mathcal{A} 's motion

One Choice for \mathbf{U}_{rep} :

$$\mathbf{U}_{rep}(\mathbf{q}) = \begin{cases} \frac{1}{2}\eta\left(\frac{1}{\rho(\mathbf{q})} - \frac{1}{\rho_0}\right) & \text{if } \rho(\mathbf{q}) \leq \rho_0 \\ 0 & \text{if } \rho(\mathbf{q}) > \rho_0 \end{cases}$$

where

- $\rho(\mathbf{q})$ is minimum distance from \mathcal{CB} to \mathbf{q} , i.e., $\rho(\mathbf{q}) = \min_{\mathbf{q}' \in \mathcal{CB}} \|\mathbf{q} - \mathbf{q}'\|$
- η is a positive scaling factor
- ρ_0 is a positive constant – *distance of influence*

So, as \mathbf{q} approaches \mathcal{CB} , $\mathbf{U}_{rep}(\mathbf{q})$ approaches ∞

The Repulsive Force $\vec{F}_{rep}(\mathbf{q}) = -\nabla U_{rep}(\mathbf{q})$ for convex \mathcal{CB}

(unrealistic) Assumption: \mathcal{CB} is a single convex region

$$\begin{aligned}
 \vec{F}_{rep}(\mathbf{q}) &= -\nabla U_{rep}(\mathbf{q}) \\
 &= -\nabla \left(\frac{1}{2} \eta \left(\frac{1}{\rho(\mathbf{q})} - \frac{1}{\rho_0} \right)^2 \right) \\
 &= -\frac{1}{2} \eta \nabla \left(\frac{1}{\rho(\mathbf{q})} - \frac{1}{\rho_0} \right)^2 \\
 &= -\eta \left(\frac{1}{\rho(\mathbf{q})} - \frac{1}{\rho_0} \right) \nabla \left(\frac{1}{\rho(\mathbf{q})} - \frac{1}{\rho_0} \right) \\
 &= -\eta \left(\frac{1}{\rho(\mathbf{q})} - \frac{1}{\rho_0} \right) (-1) \left(\frac{1}{\rho^2(\mathbf{q})} \right) \nabla \rho(\mathbf{q}) \\
 &= \eta \left(\frac{1}{\rho(\mathbf{q})} - \frac{1}{\rho_0} \right) \left(\frac{1}{\rho^2(\mathbf{q})} \right) \nabla \rho(\mathbf{q})
 \end{aligned}$$

Let \mathbf{q}_c be *unique* configuration in \mathcal{CB} closest to \mathbf{q} , i.e., $\rho(\mathbf{q}) = \|\mathbf{q} - \mathbf{q}_c\|$

Then, $\nabla \rho(\mathbf{q})$ is unit vector directed away from \mathcal{CB} along the line passing through \mathbf{q}_c and \mathbf{q}

$$\nabla \rho(\mathbf{q}) = \frac{\mathbf{q} - \mathbf{q}_c}{\|\mathbf{q} - \mathbf{q}_c\|}$$

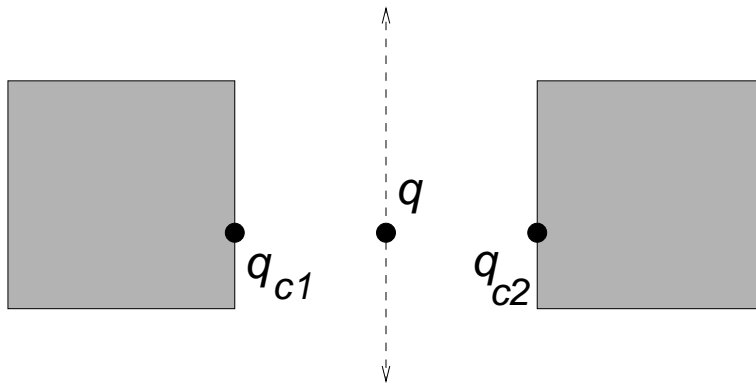
so

$$\vec{F}_{rep}(\mathbf{q}) = \eta \left(\frac{1}{\rho(\mathbf{q})} - \frac{1}{\rho_0} \right) \left(\frac{1}{\rho^2(\mathbf{q})} \right) \frac{\mathbf{q} - \mathbf{q}_c}{\|\mathbf{q} - \mathbf{q}_c\|}$$

The Repulsive Force for non-convex \mathcal{CB}

If \mathcal{CB} is not convex, $\rho(\mathbf{q})$ is differentiable everywhere except for at configurations \mathbf{q} which have more than one closest point \mathbf{q}_c in \mathcal{CB}

In general, the set of closest points \mathbf{q}_c to \mathbf{q} is $n - 1$ -dimensional (where n is the dimension of \mathcal{C})



Note: $\vec{F}_{rep}(\mathbf{q})$ exists on both sides of this line, but points in different directions (towards line) and could result in paths that oscillate

Usual Approach: Break \mathcal{CB} (or \mathcal{B}) into convex pieces

- associate repulsive field with each convex piece
- final repulsive field is the sum
- potential trouble that several small \mathcal{CB}_i may combine to generate a repulsive force greater than would be produced by a single larger obstacle
 - can weight fields according to size of \mathcal{CB}_i

Notes on Repulsive Fields

on designing \mathbf{U}_{rep}

- can select different η and ρ_0 for each obstacle region – ρ_0 small for \mathcal{CB}_i close to goal (or else repulsive force may keep us from ever reaching goal)
- if $\mathbf{U}_{rep}(\mathbf{q}_{goal}) \neq 0$, then global minimum of $\mathbf{U}(\mathbf{q})$ is generally not at \mathbf{q}_{goal}

on computing \mathbf{U}_{rep}

- pretty easy if \mathcal{CB} is polygonal or polyhedral
- really hard for arbitrary shaped \mathcal{CB}
- can try to break \mathcal{CB} into convex pieces (not necessary polyhedral) – then can use iterative, numerical methods to find closest boundary points

Gradient Descent Potential Guided Planning

Using a potential field (attractive and repulsive) for path planning...

GRADIENT DESCENT PLANNING

input: \mathbf{q}_{init} , \mathbf{q}_{goal} , $\mathbf{U}(\mathbf{q}) = \mathbf{U}_{att}(\mathbf{q}) + \mathbf{U}_{rep}(\mathbf{q})$, and $\vec{F}(\mathbf{q}) = -\nabla\mathbf{U}(\mathbf{q})$

output: a path connecting \mathbf{q}_{init} and \mathbf{q}_{goal}

1. let $\mathbf{q}_0 = \mathbf{q}_{init}$, $i = 0$
 2. if $\mathbf{q}_i \neq \mathbf{q}_{goal}$
 then $\mathbf{q}_{i+1} = \mathbf{q}_i + \delta_i \frac{\vec{F}(\mathbf{q})}{\|\vec{F}(\mathbf{q})\|}$ {take a step of size δ_i in direction $\vec{F}(\mathbf{q})$ }
 else stop
 3. set $i = i + 1$ and goto step 2
-

Notes/Difficulties/Issues:

- originally proposed and well-suited for on-line planning where obstacles are 'sensed' during motion execution [Khatib 86], [Koditschek 89]
- also called 'Steepest Descent' or 'Depth-First' Planning
- local minima are a major problem – recognizing and escaping ...
 – heuristics for escaping [Donald 84, Donald 87]
- step size δ_i
 - δ_i should be small enough so that no collision is possible when moving along straight-line segment $\mathbf{q}_i, \mathbf{q}_{i+1}$ in C-space, e.g., set δ_i smaller than minimum (current) distance to \mathcal{CB}
 - δ_i shouldn't let us overshoot goal
- how to evaluate $\rho(\mathbf{q})$ and $\nabla\rho(\mathbf{q})$ which appear in the equations for $\vec{F}(\mathbf{q})$, i.e., in finding the closest point of \mathcal{CB} to current configuration \mathbf{q}