Ensemble Control as a Tool for Robot Motion Planning:

Uncertainty, Optimality, and Complexity

Timothy Bretl (w/ Aaron Becker)

University of Illinois at Urbana-Champaign

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2 Linear example

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Problem Message

Motion planning

Find

$$u\colon [0, t_f] \to \mathcal{U} \subset \mathbb{R}^m$$
$$x\colon [0, t_f] \to \mathcal{X} \subset \mathbb{R}^n$$

satisfying

$$\dot{x}(t) = f(t, x(t), u(t))$$

$$x(0) = x_{\text{start}}$$

$$x(t_f) = x_{\text{goal}}$$

for free final time t_f

Motion planning under bounded uncertainty

Find

$$u\colon [0, t_f] \to \mathcal{U} \subset \mathbb{R}^m$$
$$x\colon [0, t_f] \to \mathcal{X} \subset \mathbb{R}^n$$

satisfying

$$\dot{x}(t) = f(t, x(t), u(t), \epsilon)$$

$$x(0) = x_{\text{start}}$$

$$x(t_f) = x_{\text{goal}}$$

for free final time t_f , despite bounded uncertainty

$$\epsilon \in [1 - \delta, 1 + \delta]$$

Motion planning as ensemble control

Find

$$u: [0, t_f] \to \mathcal{U} \subset \mathbb{R}^m$$

$$x: [0, t_f] \times [1 - \delta, 1 + \delta] \to \mathcal{X} \subset \mathbb{R}^n$$

satisfying

$$\begin{split} \dot{x}(t,\epsilon) &= f(t,x(t,\epsilon),u(t),\epsilon) \\ x(0,\epsilon) &= x_{\text{start}} \\ x(t_f,\epsilon) &= x_{\text{goal}} \end{split}$$

for free final time t_f and for all

.

$$\epsilon \in [1-\delta,1+\delta]$$

Take-away message

Ensemble control theory is a useful way to deal with bounded uncertainty in dynamical systems.

To steer one system with an uncertain parameter, we pretend to steer a continuous ensemble of systems, each with a particular value of that parameter.

In the examples we will consider, this approach costs us nothing in terms of computational complexity.

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4 Conclusion

Model Analysis Results

A driven harmonic oscillator

• This system is linear and has the form

$$\dot{x} = \begin{bmatrix} 0 & 1 \\ -\epsilon & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ \epsilon \end{bmatrix} u$$
$$= Ax + Bu,$$

where
$$(x_1, x_2) = (y, \dot{y})$$
, $u = d$, and $\epsilon = k/m$.



$$\begin{bmatrix} AB & B \end{bmatrix} = \begin{bmatrix} \epsilon & 0 \\ 0 & \epsilon \end{bmatrix}$$

is full rank.



Ensemble controllability

• For unknown ϵ , consider the lifted system

$$\dot{x}(t,\epsilon) = \begin{bmatrix} 0 & 1 \\ -\epsilon & 0 \end{bmatrix} x(t,\epsilon) + \begin{bmatrix} 0 \\ \epsilon \end{bmatrix} u(t)$$

= $A(\epsilon)x(t,\epsilon) + B(\epsilon)u(t).$

• For any integer $k \ge 0$, we have

$$\begin{bmatrix} A^{2k+1}B & A^{2k}B \end{bmatrix} = \begin{bmatrix} \epsilon^{k+1} & 0 \\ 0 & \epsilon^{k+1} \end{bmatrix}.$$

 So, we can approximate any desired movement direction by a polynomial in *ε*, with error vanishing in *k*:

$$f(\epsilon) \approx \sum_{i=0}^{k-1} \epsilon^i \left(a_i \begin{bmatrix} 1 \\ 0 \end{bmatrix} + b_i \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right)$$

Control by piecewise-constant inputs (1/2)

• A discrete-time model is

$$\begin{aligned} x_d(i+1,\epsilon) &= e^{A(\epsilon)T} x_d(i,\epsilon) + \left(\int_0^T e^{As} B ds \right) u_d(i) \\ &= A_d(\epsilon) x_d(i,\epsilon) + B_d(\epsilon) u_d(i) \end{aligned}$$

• If $x_d(0, \epsilon) = 0$ then

$$x_d(2k,\epsilon) = \sum_{i=0}^{2k} A_d^i(\epsilon) B_d(\epsilon) u_d(2k-i)$$

This can be approximated by the series expansion

$$x_d(2k,\epsilon) \approx \sum_{i=0}^{k-1} \frac{1}{i!} \left(\frac{\partial^i x_d(2k,\epsilon)}{\partial \epsilon^i} \Big|_{\epsilon=1} \right) (\epsilon-1)^i$$

Control by piecewise-constant inputs (2/2)

• The result has the form

$$x_d(2k,\epsilon) = \sum_{i=1}^k {r_i \brack s_i} (\epsilon - 1)^{i-1} + O\left(|\epsilon - 1|^k\right)$$

where $r, s \in \mathbb{R}^k$ are linear in $u_d \in \mathbb{R}^{2k}$

• To achieve (x_1, x_2) with error of order k in $|\epsilon - 1|$:

$$r = \begin{bmatrix} x_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \qquad s = \begin{bmatrix} x_2 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

• The solution (2k linear equations in 2k variables) has the form

$$u_d = K_1 x_1 + K_2 x_2$$

for matrices K_1 and K_2 that can be precomputed

Model Analysis Results

Example results in simulation





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A differential drive robot with uncertain wheel radius





Scratch-drive microrobots with uncertain forward speed





Figure: Donald et al. (2006)

• For a fixed turning radius, inputs scale with forward speed

Analysis of one robot

• This system is nonlinear and has the form

$$\dot{x} = \epsilon \begin{bmatrix} \cos x_3 \\ \sin x_3 \\ 0 \end{bmatrix} u_1 + \epsilon \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u_2$$
$$= \epsilon g_1(x)u_1 + \epsilon g_2(x)u_2$$

• For known $\epsilon > 0$, this system is controllable because

$$\begin{bmatrix} [\epsilon g_1, \epsilon g_2] & \epsilon g_2 & \epsilon g_1 \end{bmatrix} = \begin{bmatrix} \epsilon^2 \sin x_3 & 0 & \epsilon \cos x_3 \\ -\epsilon^2 \cos x_3 & 0 & \epsilon \sin x_3 \\ 0 & \epsilon & 0 \end{bmatrix}$$

is full rank everywhere

Analysis of an ensemble (1/3)

• For unknown ϵ , consider the lifted system

$$\dot{x}(t,\epsilon) = \epsilon \begin{bmatrix} \cos x_3(t,\epsilon) \\ \sin x_3(t,\epsilon) \\ 0 \end{bmatrix} u_1(t) + \epsilon \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u_2(t)$$
$$= \epsilon g_1(x(t,\epsilon))u_1(t) + \epsilon g_2(x(t,\epsilon))u_2(t)$$

• Heading is not controllable, since for all ϵ

$$x_3(t,\epsilon) = x_3(0,\epsilon) + \epsilon \theta(t)$$
 where $\dot{\theta}(t) = u_2(t)$

• Eliminate heading to get a controllable subsystem:

$$\begin{bmatrix} \dot{x}_1(t,\epsilon) \\ \dot{x}_2(t,\epsilon) \\ \dot{\theta}(t) \end{bmatrix} = \epsilon \begin{bmatrix} \cos(x_3(0,\epsilon) + \epsilon\theta(t)) \\ \sin(x_3(0,\epsilon) + \epsilon\theta(t)) \\ 0 \end{bmatrix} u_1(t) + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u_2(t)$$

Analysis of an ensemble (2/3)

• Take Lie brackets to find new control vector fields:

.

$$\begin{split} [\epsilon g_1, g_2] &= \epsilon \left(\frac{\partial g_2}{\partial q} g_1 - \frac{\partial g_1}{\partial q} g_2 \right) \\ &= -\epsilon^2 \begin{bmatrix} -\sin\left(x_3(0, \epsilon) + \epsilon\theta(t)\right) \\ \cos\left(x_3(0, \epsilon) + \epsilon\theta(t)\right) \\ 0 \end{bmatrix} \\ &= -\epsilon^2 g_3 \\ [[\epsilon g_1, g_2], g_2] &= -\epsilon^3 g_1 \\ [[[\epsilon g_1, g_2], g_2], g_2] &= -\epsilon^4 g_3 \\ &\vdots \end{split}$$

Analysis of an ensemble (3/3)

• We can approximate any desired movement direction by a polynomial in *ε*, with error vanishing in *k*:

$$f(\epsilon) \approx cg_2 + \sum_{i=0}^k \left(a_i \epsilon^{2i+1}g_1 + b_i \epsilon^{2i+2}g_3\right)$$

u_1 u_2 Δt

O

$$\begin{array}{c|cc} u_1 & u_2 & \Delta t \\ \hline 0 & 1/\lambda & \lambda(j-1)\phi \end{array}$$





$$egin{array}{ccc} u_1 & u_2 & \Delta t \ \hline 0 & 1/\lambda & \lambda(j-1)\phi \ \operatorname{sign} \left(a_j'
ight) & 0 & \left|a_j'
ight| \end{array}$$

$$\begin{array}{c} & \underbrace{u_1 & u_2 & \Delta t} \\ \hline 0 & 1/\lambda & \lambda(j-1)\phi \\ & \operatorname{sign} \begin{pmatrix} a_j' \end{pmatrix} & 0 & \begin{vmatrix} a_j' \\ 0 & -1/\lambda & 2\lambda(j-1)\phi \end{vmatrix}$$





Correspondence with polynomial approximation

• The result is to achieve

$$\Delta x_1(\epsilon) = (a'_j + b'_j)\epsilon \cos(\epsilon(j-1)\phi)$$
$$\Delta x_2(\epsilon) = (a'_j - b'_j)\epsilon \sin(\epsilon(j-1)\phi)$$
$$\Delta \theta = 0$$

• With the input transformation

$$a_j'=rac{a_j+b_{j-1}}{2}$$
 $b_j'=rac{a_j-b_{j-1}}{2}$

for freely chosen $a_k, b_k \in \mathbb{R}$, we can write

$$\Delta x_1(\epsilon) = a_j \epsilon \cos\left(\epsilon(j-1)\phi\right)$$
$$\Delta x_2(\epsilon) = b_{j-1}\epsilon \sin\left(\epsilon(j-1)\phi\right).$$

Sequence of motion primitives (1/3)

• For $a_{k+1} = 0$, the result after k + 1 primitives is

$$\Delta x_1(\epsilon) = \sum_{j=1}^k a_j \epsilon \cos(\epsilon(j-1)\phi)$$

 $\Delta x_2(\epsilon) = \sum_{j=1}^k b_j \epsilon \sin(\epsilon j \phi)$

• This can be approximated by the series expansions

$$\Delta x_1(\epsilon) \approx \sum_{i=0}^{k-1} \frac{1}{i!} \left(\frac{\partial^i \Delta x_1}{\partial \epsilon^i} \Big|_{\epsilon=1} \right) (\epsilon - 1)^i$$
$$\Delta x_2(\epsilon) \approx \sum_{i=0}^{k-1} \frac{1}{i!} \left(\frac{\partial^i \Delta x_2}{\partial \epsilon^i} \Big|_{\epsilon=1} \right) (\epsilon - 1)^i$$

Sequence of motion primitives (2/3)

• The result has the form

$$egin{split} \Delta x_1(\epsilon) &= \sum_{i=1}^k r_i \left(\epsilon-1
ight)^{i-1} + O\left(|\epsilon-1|^k
ight) \ \Delta x_2(\epsilon) &= \sum_{i=1}^k s_i \left(\epsilon-1
ight)^{i-1} + O\left(|\epsilon-1|^k
ight) \end{split}$$

where $r, s \in \mathbb{R}^k$ are linear in $a, b \in \mathbb{R}^k$

• To achieve $\Delta x_1 = \Delta x_2 = 1$ with error of order k in $|\epsilon - 1|$:

$$r = s = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Model Analysis Results

Sequence of motion primitives (3/3)

- Require exactly k + 1 primitives to achieve kth-order error
- Precompute a, b as 2k linear equations in 2k variables
- For $\phi = \pi/2$, this can be done in closed form
- By linearity, $a\Delta x_1$ and $b\Delta x_2$ reach arbitrary Δx_1 and Δx_2
- "Planning" means computing piecewise-constant inputs

$$egin{aligned} &a' = rac{1}{2} \left(egin{bmatrix} a \ 0 \end{bmatrix} \Delta x_1 + egin{bmatrix} 0 \ b \end{bmatrix} \Delta x_2
ight) \ &b' = rac{1}{2} \left(egin{bmatrix} a \ 0 \end{bmatrix} \Delta x_1 - egin{bmatrix} 0 \ b \end{bmatrix} \Delta x_2
ight). \end{aligned}$$

• This approach does *not* require sampling ϵ

Example results in simulation



Scaled primitives get you everywhere "for free"



Example results in experiment



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Connections

- NMR spectroscopy and imaging (Brockett, Khaneja, Li, Altafini, Beauchard, Coron, Pereira da Silva, Rouchon, etc.)
- Robust control (Dullerud and Paganini, Singer and Seering, Fischer and Psiaki, etc.)
- Sensorless manipulation (Erdmann, Mason, Goldberg, Lynch, Murphey, Akella, van der Stappen, Moll, etc.)
- POMDP planning (Hsu, Hutchinson, Roy, Thrun, etc.)
- Optimal control of micro/nano-robot teams (under review)
- Control-theoretic approach to manipulation of deformable objects (in preparation)
- BMIs based on inverse optimal control

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Connections

Questions?



Connections

Connection to NMR spectroscopy and imaging

- Need to manipulate an ensemble of $\approx 10^{23}$ nuclear spins, each governed by the Schrödinger equation
- Control input changes the potential energy in the system Hamiltonian (e.g., by applying electromagnetic pulses)
- One model is

$$\frac{dx(t,s)}{dt} = \left(A(s) + \sum_{i} u_{i}B_{i}(s)\right)x(t,s)$$

- "*s*" describes variation in *A* and *B_i* from Larmor dispersion (in natural frequencies), rf inhomogeneity (in strength of the applied radio frequency), and relaxation rates
- Is it possible to steer from one state to another?