Model-Based Optimization for Intelligent Robot Control

Tom Erez Motion Control Lab Computer Science University of Washington

Goal:

optimal control of humanoid robots

- Quick, autonomous adaptation to novel circumstances.
- Unified framework for different tasks (e.g. grasping, walking).
- User guidance should be easy and intuitive.

Challenges

- **Simulation**: torques, friction, contact.
- **Optimization**: nonlinear, nonconvex, high-DoF.
- **Systems**: estimation, integration, feedback control.
- **Human operator**: flexibility, visualization, interfaces.

MPC in MuJoCo

- A new physics engine: MuJoCo (Multi-Joint simulation with Contacts).
- An optimization framework around MuJoCo that can operate in real-time.
- An integrated system for controlling articulated robots.



Optimal Control state \mathbf{X} $\ell(\mathbf{x},\mathbf{u})$ cost **Dynamics** Agent $\mathbf{x}' = \mathbf{f}(\mathbf{x}, \mathbf{u})$ future $\sum \ell(\mathbf{x},\mathbf{u})$ $\min_{\mathbf{U}}$ present u contro



Trajectory Optimization

Trajectory Optimization state **X**, control **U**

Dynamics:
$$\mathbf{x}' = \mathbf{f}(\mathbf{x}, \mathbf{u})$$
 Dynamics cost Agent
Cost: $\ell(\mathbf{x}, \mathbf{u}), \Omega(\mathbf{x}_{\text{final}})$ control

Trajectory Optimization

State \mathbf{X} , control \mathbf{U}

Dynamics: $\mathbf{x}' = \mathbf{f}(\mathbf{x}, \mathbf{u})$ Cost: $\ell(\mathbf{x}, \mathbf{u}), \Omega(\mathbf{x}_{\text{final}})$

Initial state: \mathbf{x}_0

Control $\mathbf{u}_1, \mathbf{u}_2 \dots \mathbf{u}_N$ sequence:

(Single shooting / indirect optimization) 10

Trajectory Optimization



 $\min_{\mathbf{u}_1...\mathbf{u}_N} \left[\sum_{k=1}^N \ell(\mathbf{x}_{k-1}, \mathbf{u}_k) + \Omega(\mathbf{x}_N) \right]_{\mathrm{II}}$

One Plan is not Enough

- Modeling errors
- Estimation errors
- Dynamic environment

Model-Predictive Control



- There is always a plan.
- The plan is constantly updated.
- Only the initial portion is ever executed.

Tassa, Erez and Smart, NIPS 2008 Tassa, Erez and Todorov, IROS 2012

Modeling Errors



The Swimmer



Tassa, Erez and Smart, NIPS 2008

Physics Simulation



differentiable

Todorov, Erez and Tassa, IROS 2012

Contact Modeling

- Non-convex
- Non-smooth
- NP-hard





Contact dynamics

Coulomb friction (NP hard)

$$v = Af + b$$

$$v_N \perp f_N$$

$$||v_T|| \perp \mu f_N - ||f_T|$$

$$v_T = \alpha f_T, \ \alpha \le 0$$

$x \perp y$	complementarity: $x \ge 0, y \ge 0, xy = 0$
A	contact inverse inertia: $A = JM^{-1}J^T$
b	contact velocity before impulse
f	contact impulse
v	contact velocity after impulse

Define the contact impulse by minimizing contact-space kinetic energy $\frac{1}{2}v^T A^{-1}v$, subject to $v_N \ge 0$, $f_N \ge 0$, $\mu f_N \ge ||f_T||$ for each contact. Replace the penetration constraint with a penalty function $d_V(v)$. Forward contact dynamics: $(A,b) \rightarrow (f, v = Af + b)$

$$f^* = \arg\min_f \frac{1}{2} f^T A f + f^T b + d_V (A f + b)$$

Inverse contact dynamics: $(A, v) \rightarrow (f, b = v - Af)$

 $f^* = \arg\min_f f^T (v + A \nabla d_v(v))$

Todorov, *ICRA* 2011

N

 T_1

 T_2



Timing (Single Core)

One dynamics step (35 DOF, 8 contacts)

0.01 ms = 100,000/sec

Harnessing Parallelization

One optimization step

Single i7 core:

Quad-core i7:

8-core Xeon (Amazon EC2): 9 updates/second

33 updates/second

50 updates/second

Minimum Policy Lags Normalized Frequency (%) Stand (1100 Samples) All Lags (2370 Samples) 0.1 0.01

Policy Lag (ms)

Harnessing Parallelization

- GPGPU
- Intel's Xeon Phi co-processor



System integration

- Specification language for models and cost functions, transitions and alterations.
- Visualization for monitoring the system's state – timing, estimation, prediction errors, optimization status.
- GUI switching between tasks, adjusting weights.



Future work

- Estimation with contact
- Combining direct optimization to minimize cost tweaking
- Learning from experience
- "Instincts" low-level overriding controllers
- Stiff, geared robots
- Pneumatic systems



Emo Todorov

Thank you!



Yuval Tassa