Learning manipulation with multi-fingered robot hands from human demonstration

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Overview

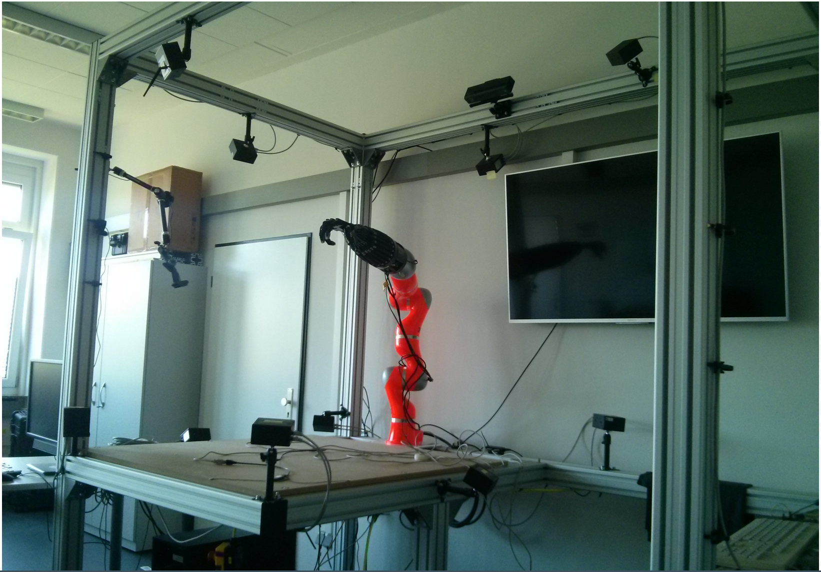
1. Hardware setup
2. Motion tracking
3. Pneumatic robot control
4. Learning from humand demonstration
5. Learning + kinodynamic online trajectory optimization
6. Videos
7. Future work

CML Demo in September

- Open "medicine bottle"
- Humanoid robot hand
- Learning from human demonstration
- Machine learning / neural networks
- Crossmodal Learning

Hardware setup

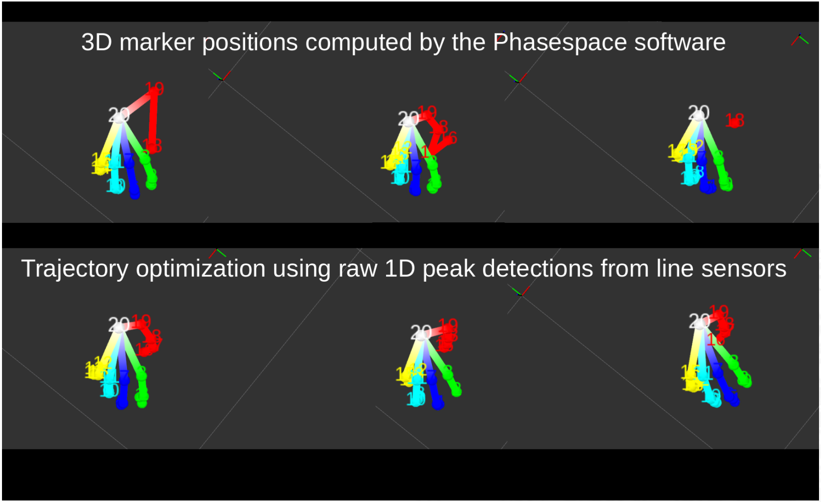
- KUKA LWR arm, pneumatic C5 hand, Phasespace Impulse X2



Phasespace

- Phasespace Impulse X2
- Line Cameras
- High FPS, up to 960 Hz
- Output:
  - 3D marker positions
  - 6D rigid body poses
  - 1D marker positions on line sensors
- 3D positions inaccurate
- Custom reconstruction

Tracking


3D marker positions computed by the Phasespace software
Trajectory optimization using raw 1D peak detections from line sensors

Tracking glove and bottle

Pneumatic Robot Control

Previous

- Position error => Proportional controller => Valve commands
- Hardware support on Shadow hand valve boards
- Unstable under contact

New

- Position error => P controller => Forces
- Forces => P controller => Valve commands
- Current state-of-the-art method
- Stable under contact
- No hardware support, run in software

Hand / Bus System

Previous

- Hardware: PC => Ethernet => Second PC => Parallel port => Converter => CAN bus => Shadow hand
- Software Software: ROS + network client + network server + Shadow software
- Too slow and unreliable to run controllers in software

New

- Hardware: PC => USB => CAN bus
- Software: Roscontrol + custom driver
- Fast enough to run controllers in software

Learning from humand demonstration

Sub-tasks

- Record demonstrations (see above)
- Learning
- Transfer from human to robot

- First record demonstrations and pre-process data, then learn
- How to combine learning and transfer?

Learning + Transfer, 1/5, Retargeting + Policy Cloning

- First map marker positions to matching robot states (IK or trajectory optimization), then learn robot joint angles
- Problem: Redundancies
- Problem: Accurate non-linear regression using neural networks

- Policy cloning: $state2 = policy(current\_state, observations)$
- Problem: unstable, errors accumulate over time, but network has only been trained on single time steps

Learning + Transfer, 2/5, Learned Transfer

- Also learn human-to-robot mapping from demonstrations
- E.g. robot assumes random poses, human imitates them, invert and learn human-to-robot mapping through supervised learning
- Popular approach in literature
- Problem: requires huge amounts of training data
- Problem: usually inaccurate

Learning + Transfer, 3/5, Reinforcement Learning

- End-to-end reinforcement learning
- Input marker positions, learn joint angles or velocities
- Network could learn redundancy resolution
- Rewards across multiple time steps => robust policy
- Could improve policy autonomously
- Reinforcement learning currently slow and inefficient (even in simulation), good differentiable robot simulators not (yet) available (future work?)
- Network would have to learn technical details about a specific robot
- Physics equations already exist / why learn them?
- Want to focus on (higher-level) manipulation problem

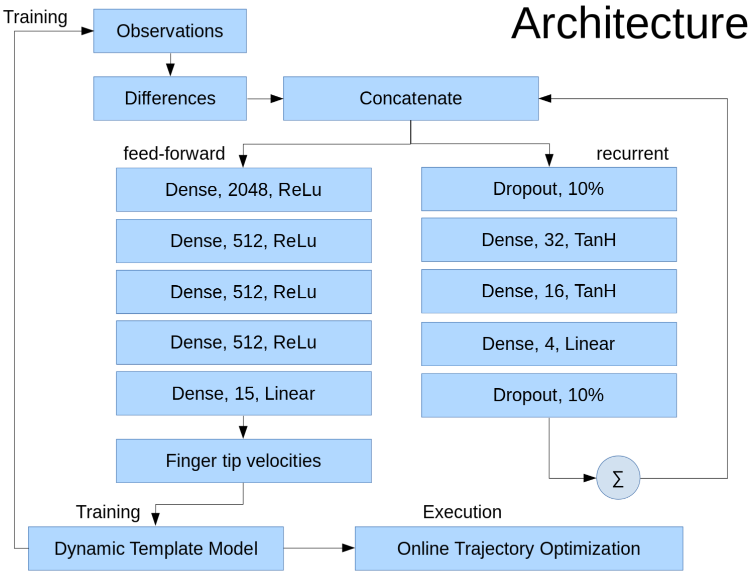
Learning + Transfer, 4/5, Inverse Optimal Control

- Learn a cost function + trajectory optimization
- Assume that human actions are close-to-optimal according to a reward function, try to learn reward function
- Usually requires accurate models of humans and objects
- "Inverse Reinforcement Learning"
- Often solved using (inefficient) reinforcement learning methods ("inverse reinforcement learning")
- Ill-posed problem: many different reward functions could explain a specific action
  - Strong regularization / sparsity
  - How to represent the cost function?
  - Neural network = very general but many variables, hard to find a meaningful cost function from few examples
  - Huge number of demonstrations usually required for non-trivial tasks

Learning + Transfer, 5/5

- Simplified differentiable template model: 5 points = finger tip positions, learn 3D cartesian velocity commands
- Online trajectory optimization
- Compromise between 3 and 4: Position goals = simplified template model (3) or learned cost function (4)
- Less ill-posed than general IRL, differentiable, can be solved efficiently
- Does not have to learn technical details about a specific robot, network can focus on high-level aspects related to manipulation, learned policies mostly robot-independent
- Consider multiple time steps and use differentiable model to propagate gradients back in time to improve robustness (s. option 1)
- Prediction + trajectory optimization for redundancy resolution
- Fast trajectory optimizer needed, online, many DOF: 20 (hand) + 7 (arm)

Architecture



Training

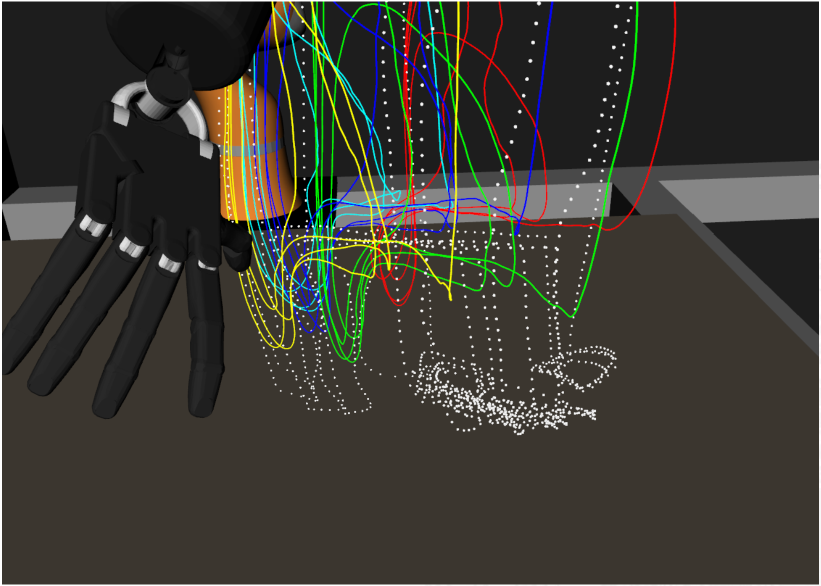
- Train with simplified dynamic template model on complete trajectories
- Minimize mean absolute error between predicted trajectories and demonstrations
- Reset robot states to recorded tracking data at randomly selected time steps
  - Many resets = faster learning, but less stable policy
  - How to choose reset probability?
  - Per-trajectory reset density $= c^{rand()}$
  - Per-sample reset probability $= rand() * density$
  - => Parameter choice simple (exponential, from almost zero to almost 1)

Pose Invariance and Augmentation

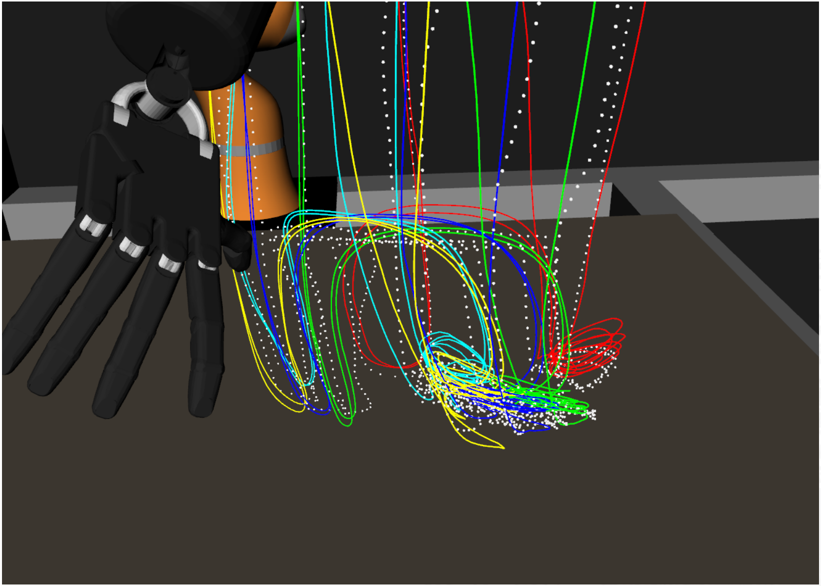
- Input: relative finger-to-object vectors
  => position invariance
- Random rotations (augmentation)
  => rotation invariance
- Random hand/object offsets (augmentation)
  => Learn to control hand pose relative to object
  => Generalize approach motions
- Arbitrary random mutations (augmentation)
  => Learn to control finger poses relative to each other

- Per-trajectory random scaling: $c^{rand()}$
- Per-sample offsets: $gaussian() * scaling$

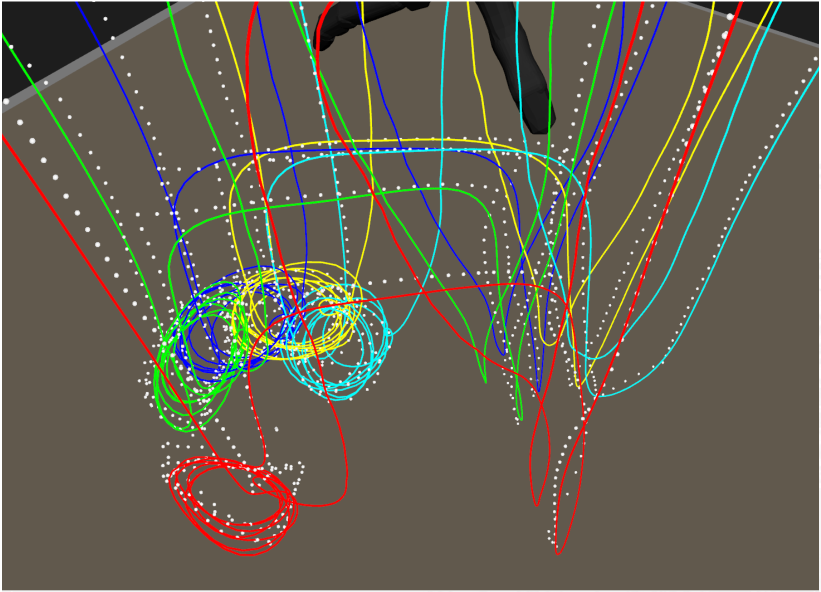
Learning



Learning



Learning



Trajectory Optimization

- Online
- Kinematics + dynamics
- Many degrees of freedom: 20 (hand) + 7 (arm)
- Doing it efficiently - interesting problem
- Custom trajectory optimizer
- Goal programming interface
  - PositionGoal (finger tips)
  - MinimalAccelerationGoal (smooth trajectories)
  - CollisionAvoidanceGoal (2x: hard + soft w. padding)
  - etc.

Trajectory Optimization

- Sequential Quadratic Programming
  - Locally approximate non-linear trajectory optimization problem via linearly constrained quadratic equations
  - Solve QP (many existing methods available)
  - Repeat until convergence
  - One of the standard methods for solving non-linear problems
- Several different solvers
  - Interior-point method (usually fastest, as expected)
  - Penalty method (ok for simple problems)
  - Active-set method (interesting but in practice often slow)
  - Projected Gauss-Seidel (sometimes faster for highly under-determined problems)
  - EnsembleQP: Run different methods in parallel, take first valid solution

Videos

Video

Videos

Video

Videos

Video

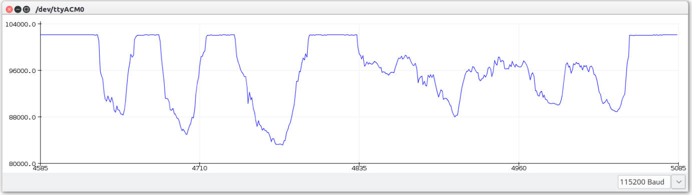
Videos

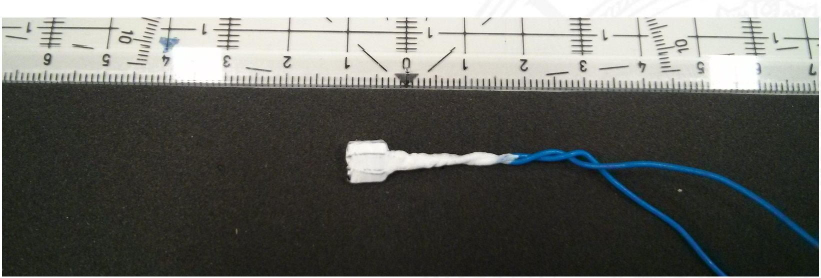
Video

Future Work - Bottle Opening

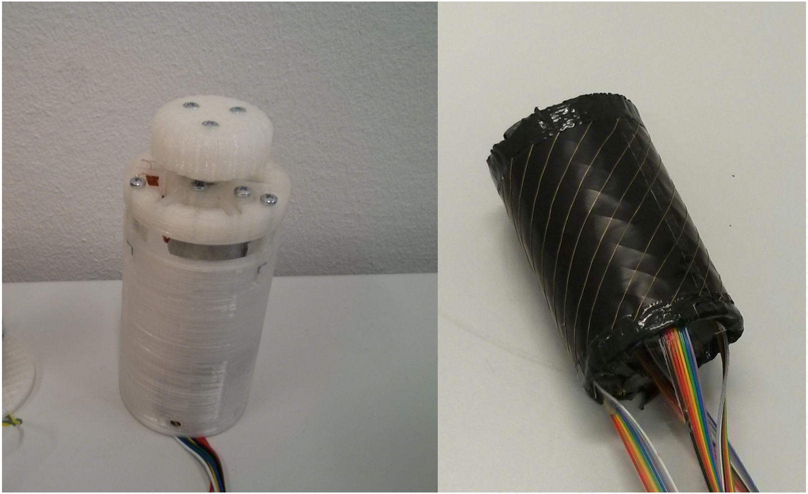
- Try new recurrent network on robot
- How fast can the robot do it?
- Object detection
- Different bottle types and sizes
- Different strategies?
- Collect data from different test subjects
- Crossmodal learning, instrumented objects, tactile glove

- Tactile sensor



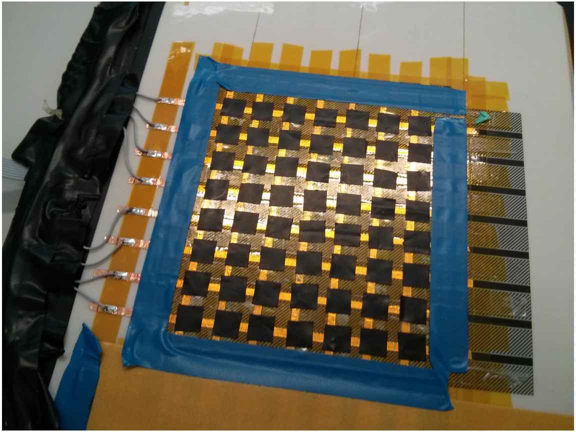


- Torque sensor, motor, tactile matrix



Tactile Sensing

- Tactile matrix



Tactile Sensing

- Tactile glove prototype

Future Work - Trajectory Optimization

- Dual interior points for collision prevention
  - Interior-point methods known for decades
  - Currently popular robot trajectory optimizers often use penalty-like formulations
  - Dual interior points = simultaneously solve for objectives and constraint feasibility, starting point does not have to be feasible
- Weights AND hard priorities
  - Collisions > position goals > smoothness
- Special contact models for planning (e.g. Contact Invariant Optimization, results currently unrealistic + bad scalability)
- Exploit problem structure
  - Hessian (H) / model (M) and problem (P): $H = M^T P^T P \; M$
  - P: usually $O(n)$ sparse, maybe pre-multiply
  - M: worst case $O(n^2)$ for n links but sparse $O(n)$ internal structure (kinematic tree)
  - Auto-diff through kinematic tree inefficient (rotations)
  - High-performance matrix replacement

Future Work - Learning From Simulation

- Discover manipulation strategies autonomously
- Standard RL slow
- Run in simulation, still slow
- RL = useful for unknown environments
- Simulated environments exactly known (even with pseudo-random "domain randomization")
- Simulation + learning = single well-defined optimization problem (vs. RL algorithm), but non-convex
- Supervised learning = usually convex? (exception: sparse regularization)
- Many learning problems in robotics hard-to-solve non-convex optimization problems (manipulation + locomotion)
- Convex = "easy", non-convex = "hard"

Future Work - Learning From Simulation

- Can we convexify robot simulation?
- Quite complex, full and provable convexification unlikely
- Find something that works in practice
- In machine learning: neural networks not provably convex, but can be trained through convex optimization in practice
- Soft contact models
- Relax physical consistency, simultaneously optimize for rewards and physical consistency
- Walking = fly from A to B, then learn to move legs via soft ground model = learning to walk via convex optimization !!!
- Manipulation?
- Soft contact models + physical consistency relaxation -> solve efficiently through convex optimization