Data-Driven Manipulation with a Simple Hand

Georgia Institute of Technology
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Alberto Rodriguez
Talk Structure

I - Probabilistic Data-driven Manipulation

II - The MLab Hand

III - Shape Design

Empirical

Analytical
Probabilistic Manipulation
Probabilistic Manipulation

• Manipulation traditionally an assumption driven discipline:
  ✓ Find assumptions so that the problem is “solvable”.
  ✓ Algorithms, planners that seek correctness or completeness.
  ✓ But: • When are those assumptions satisfied?
    • 100% is not always necessary. Sometimes too expensive.

• Recently, approached from data-driven learning perspective:
  ✓ Data-driven helps bridge the gap between models and reality.
  ✓ But: • Lost the ability to guarantee performance.

• Real applications will need from both.
Manipulation Scenario

- What does the hand know about the object?
- What does the brain need to know about it?

Probabilistic Manipulation - The MLab Hand - Shape Design
Balance a Cylinder

Probabilistic Manipulation - The MLab Hand - Shape Design
Balance a Cylinder

Easy if we know exactly where the cylinder is.

Probabilistic Manipulation - The MLab Hand - Shape Design
Balance a Cylinder

• But what if the exact position of object in hand is not known?

• The hand has to tell the brain where it is.

Task
Balance a cylinder using only in-hand information, and estimate the probability of failure.

Probabilistic Manipulation - The MLab Hand - Shape Design
Performance depends on lots of factors:

- more/less sensors?
- more/less noisy sensors?
- smaller/larger base?
- more/less friction in base?

We need a measure of:

✓ How well we know the pose of the object. (What the hand tells the brain)

✓ How well we should know the pose to execute the task. (What the brain expects from the hand)
Probabilistic Model

- How do we capture that information?

\[ P(\text{success}|\text{sensors}) \cdot P(\text{success}|\text{pose}) \cdot P(\text{pose}|\text{sensors}) \]

- Sensing Capabilities (*What the hand tells the brain*)

- Task Requirements (*What the brain expects from the hand*)

Probabilistic Manipulation - The MLab Hand - Shape Design
Probabilistic Model

- Optimal action/object location to take.
- Estimate Probability of Success.

Probabilistic Manipulation - The MLab Hand - Shape Design
Pose parametrization

- Flat against the palm
- Parametrization \((r, \theta)\)
- 3 most distinctive grasps.
Sensing Capabilities

\[ P(\text{pose} | \text{sensors}) = \frac{P(\text{pose} | \text{sensors}) \cdot P(\text{pose})}{P(\text{sensors})} \]

(Posterior) \hspace{2cm} (Likelihood) \hspace{2cm} (Prior)

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Sensing Capabilities

\[ P(\text{pose} | \text{sensors}) \]
Task Requirements

\[ P(\text{success}|\text{pose}) \]

- **Bernoulli random variable.**
- **Gaussian Process Regression.**
Task Requirements

\[ P(\text{success} | \text{pose}) \]
Probabilistic Model in Action

Probabilistic Manipulation - The MLab Hand - Shape Design
Probabilistic Model: Validation

Based on 500 tests

Abort below a certain threshold on the probability of success

Probabilistic Manipulation - The MLab Hand - Shape Design
Probability of Failure

• Ways to approach and manage failure:
  ✓ Predict beforehand (just shown).
  ✓ Predict meanwhile.
    • Preliminary work extending to continuously track the probability of failure and abort anytime during task execution.
    • Early Abort and Retry can be optimized to minimize time to success.
  ✓ Detect after the fact.

• Next step: How to react to low probability:
  ✓ Retry or Regrasp.
Probabilistic Regrasp

Example task: Use a screwdriver

- Set of grasps and candidate regrasps.
- Probabilistic modeling of each regrasp transitions.
Summary Goal

- Robots that are aware of what is happening,
- Capable of predicting the outcome of their actions,
- All as seen by the actuators and sensors in the hand,
- Based on probabilistic models.
Empirical Models

• Is learning and data-driven the solution?
  ✓ Great to close the gap between models and reality, but ...
  ✓ Size of the manipulation problem is too big for learning.
  ✓ Search needs to be strategically focused:
    One of the roles of analytical models.
The MLab Hand
Hand Concept

- Circular palm.
- Three rigid fingers.
- Compliantly connected to a single actuator.
Hand Concept

[“Auton. Manip. with a General-Purpose Simple Hand” - IJRR 2012]
The MLab Hand

- Sensorized
- Robust
  ✓ Mechanics and sensors.
- Low cost.
- Replaceable fingers.
- Open Source.
The MLab Hand
Transmission

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Transmission

Probabilistic Manipulation - The MLab Hand - Shape Design
Robust Compliance

Fingers

Palm

Probabilistic Manipulation - The MLab Hand - Shape Design
Robust Sensing

Fingers

Palm

Probabilistic Manipulation - The MLab Hand - Shape Design
Replaceable Fingers
Shaping Fingers
Mechanical Function and Shape
Mechanical Function and Shape
Complex vs Simple Hands

Probabilistic Manipulation - The MLab Hand - Shape Design
From Function to Shape

- Two step approach:

1. *From function to contact*: Represent mechanical function as a set of contact constraints.

2. *From contact to shape*: Derive shape from a set of contact constraints.
From Function to Contact

- Fixed the actuation mechanism, shape determines where contact between finger and object happens.

- Design principle: Chose adequate contact points.

- Represent mechanical function or task as a set of contacts.
From Contact to Shape

[“Grasp Invariance” - IJRR 2012]

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From Contact to Shape

[“Grasp Invariance” - IJRR 2012]

Probabilistic Manipulation - The MLab Hand - Shape Design
Pose Invariance

[“Grasp Invariance” - IJRR 2012]

Probabilistic Manipulation - The MLab Hand - Shape Design
Grasp Stability
Grasp Stability

Probabilistic Manipulation - The MLab Hand - Shape Design
The Fingers of the MLab Hand
The Fingers of the MLab Hand

Probabilistic Manipulation - The MLab Hand - Shape Design
The Fingers of the MLab Hand

- Enveloping grasps

- Fingertip grasps

Probabilistic Manipulation - The MLab Hand - Shape Design
Next Steps

• Generalization to any planar 1DOF mechanism.
• Generalization to 3D mechanisms.
• Application to locomotion:
  ✓ Synthesis and analysis of gates.
  ✓ Feet design.
Shapes
Thanks!!