Grasping – from Human to Robot

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Outline

- Learn grasping from human
  - Motion
  - Force
  - Interaction

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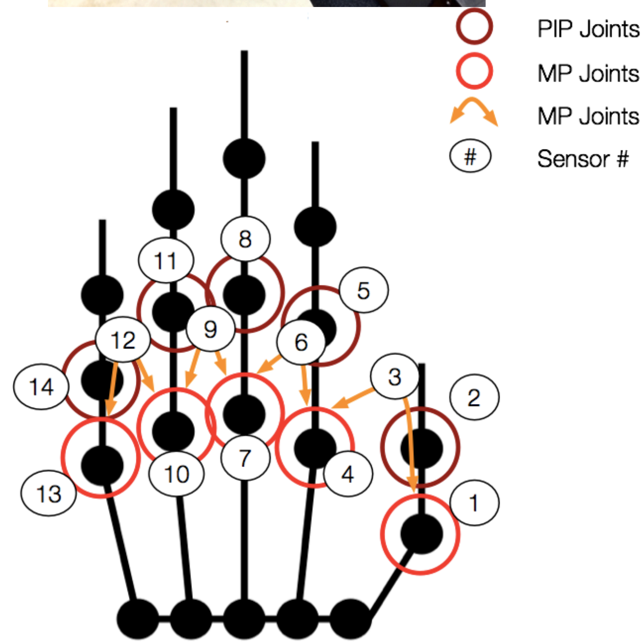
Motivation

- Develop a tool to extract and represent both hand synergy and grasp motion dynamics features
- Compare different grasp motions
- Find nature clustering of similar grasp motions
- In terms of grasp motion trajectory
- Similar grasp motion may indicate similar control
- Motion features and clustering may provide insight on human grasping strategies and be useful for robotic grasping control

Grasp Motion Data Collection

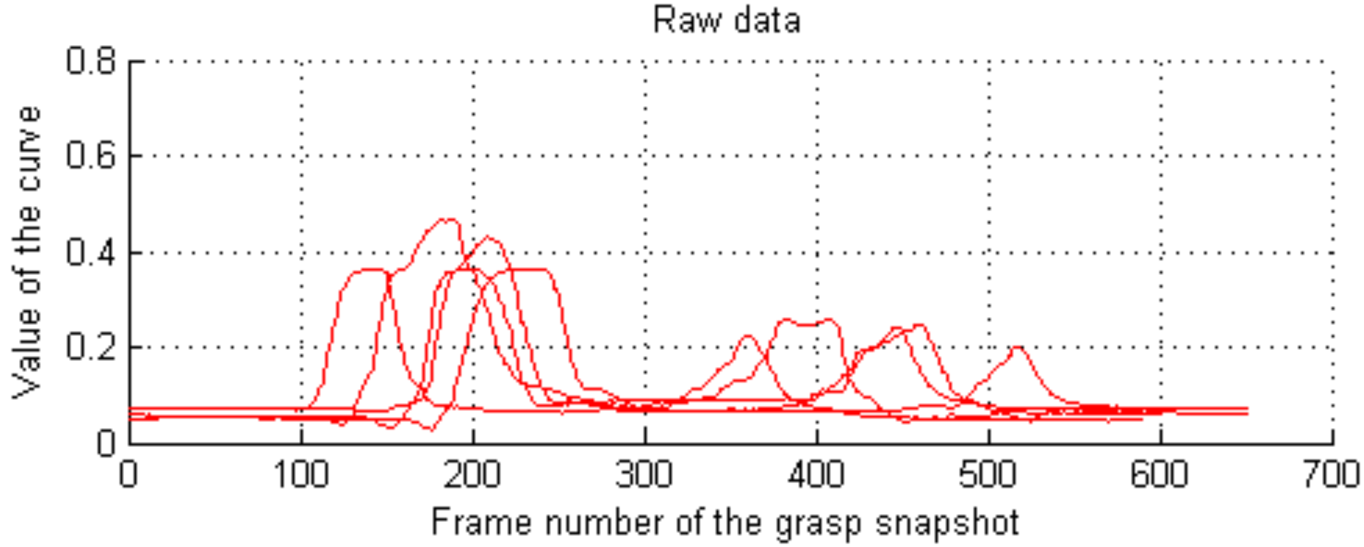
5DT
Dataglove

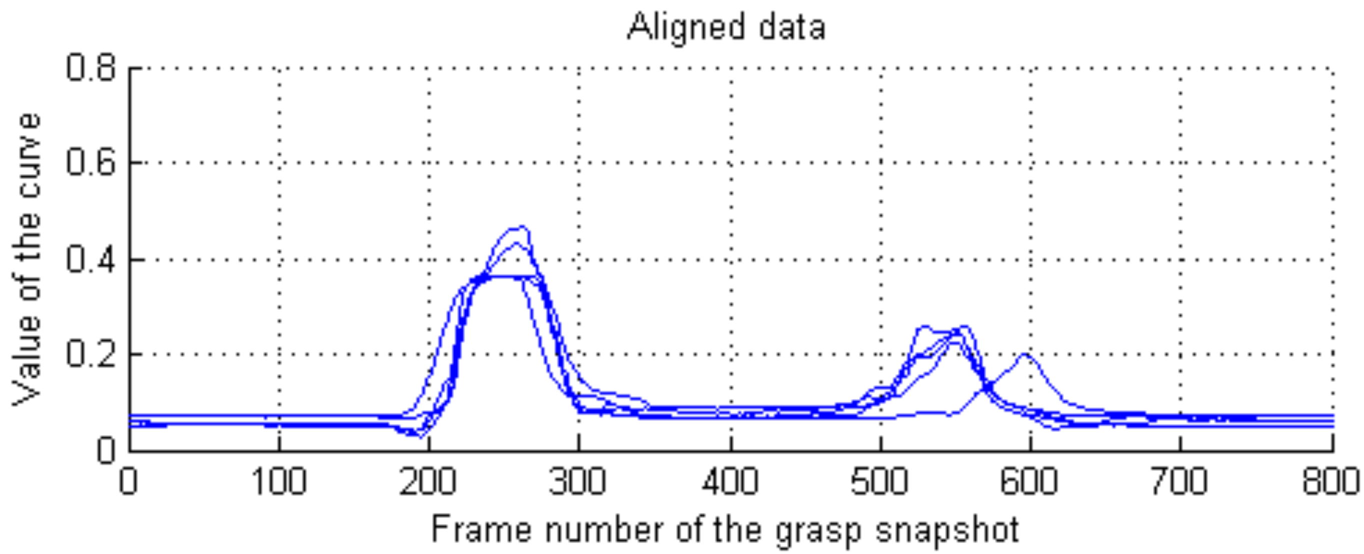


Initial Data

- Five participants
- Nine different objects with 15 Cutkosky types of grasp
- Five trials each type
- Measure 14 joints -- 14-DOF data
- 14 dimensional time series data -- 60 Hz sampling

Motion Alignment



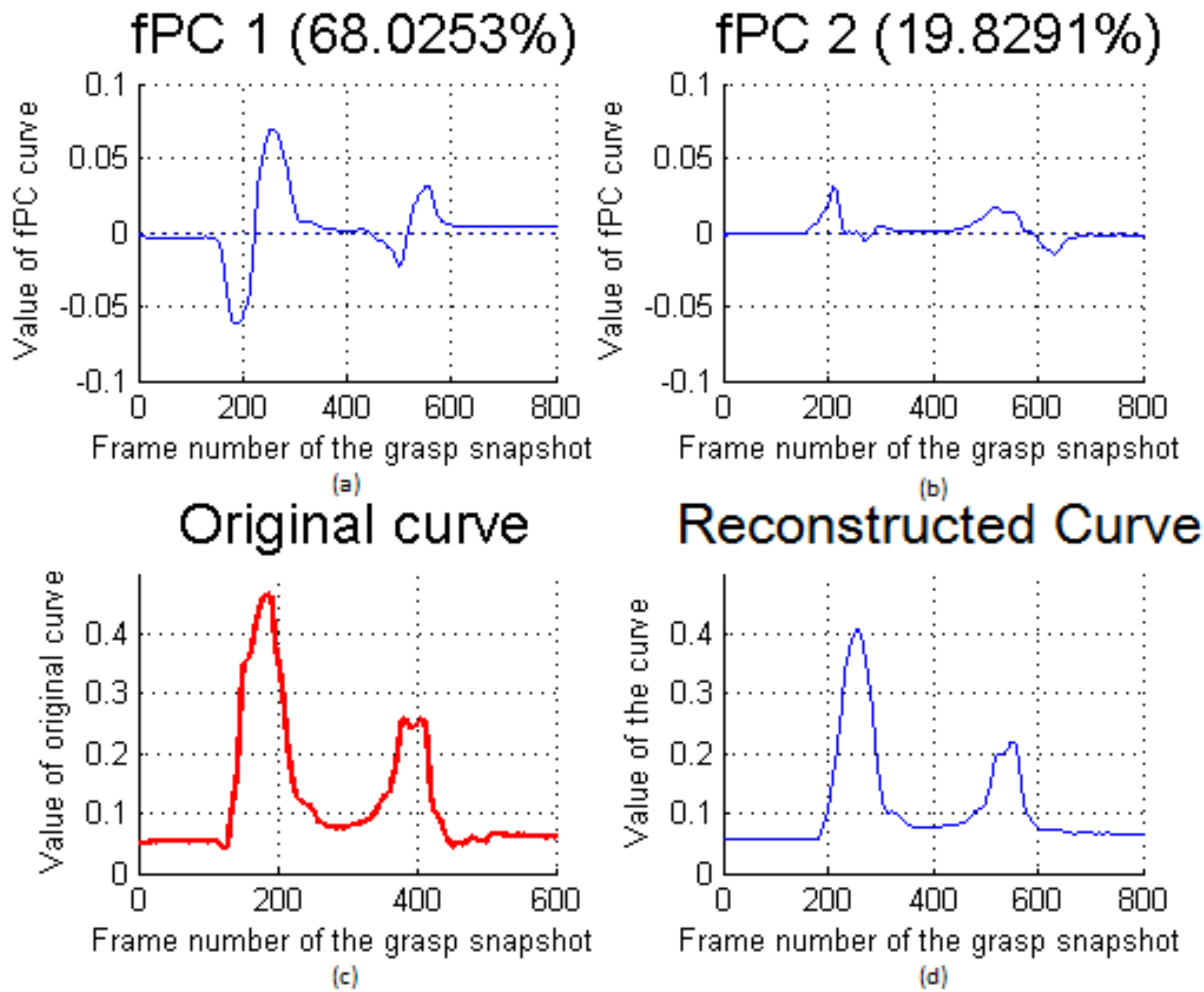


Applied dynamic time warping

Represent Motion Data with PCA+fPCA

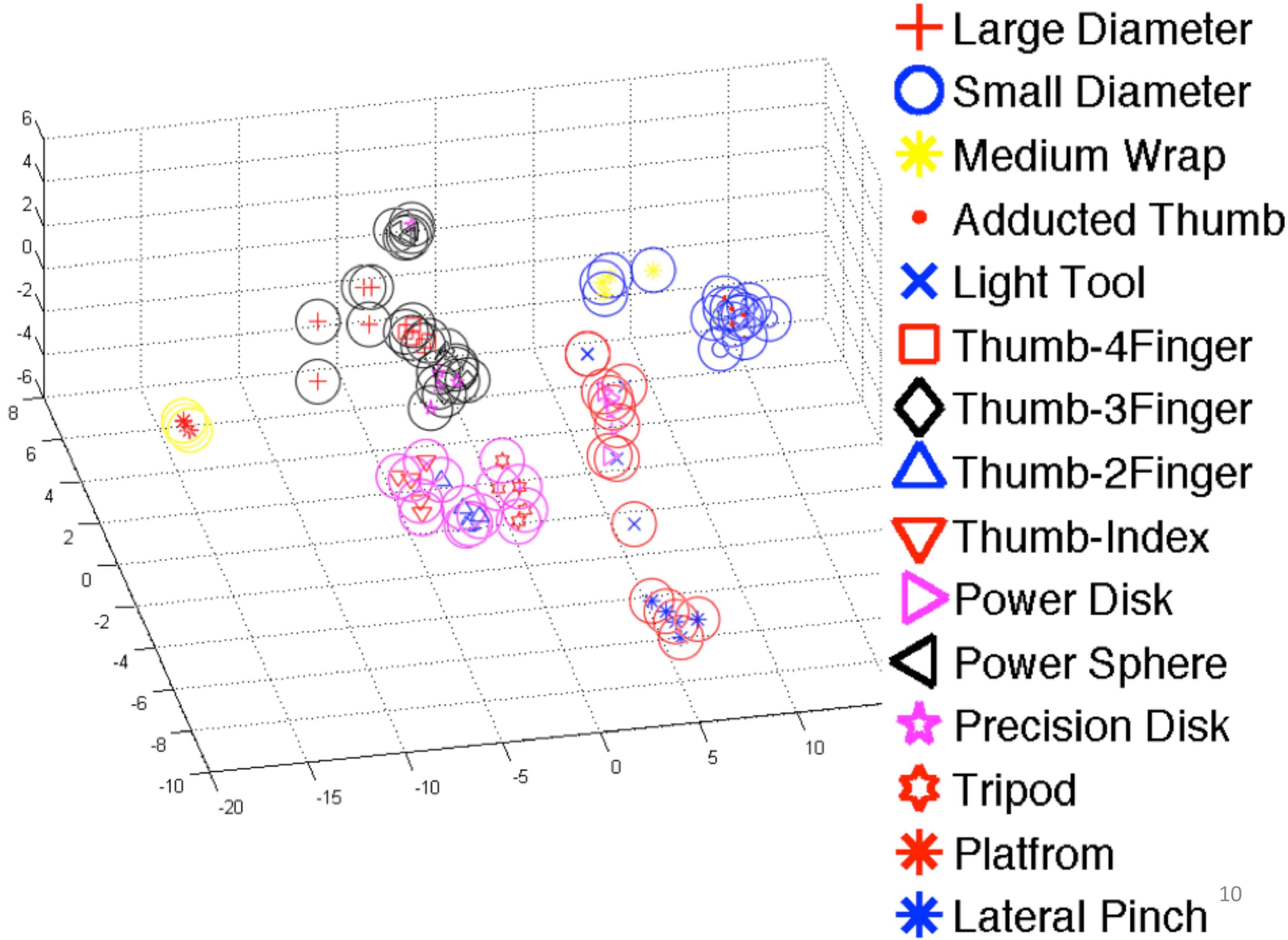
- Two fPCA scores for each of the three PCA scores
- A continuous grasp motion is represented with six variables
- With two fPCs for each of the three PCs
- A motion curve is represented as a point in the six dimensional space

FPCA



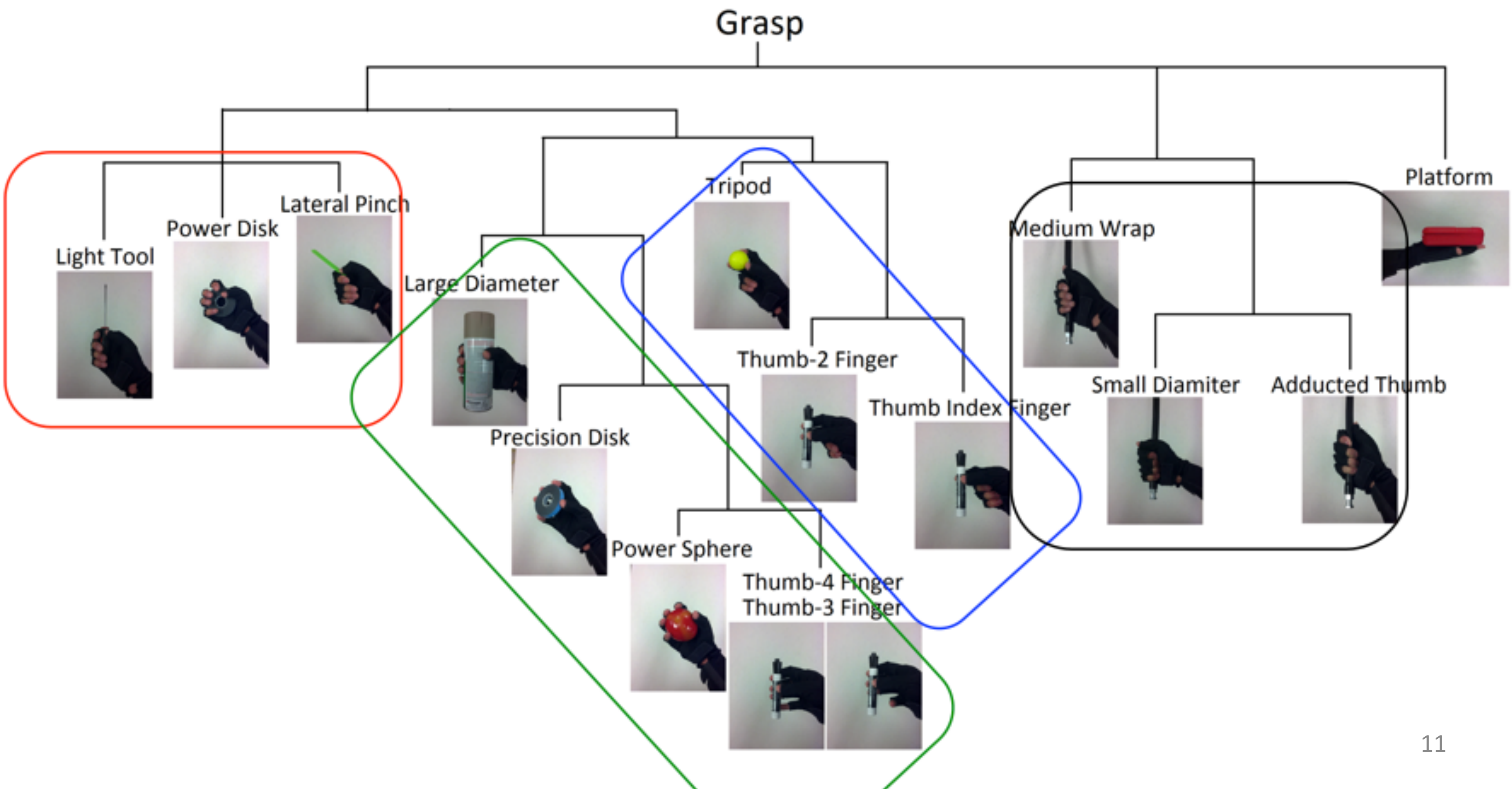
fPC 1 (68.0253%)
fPC 2 (19.8291%)
Value of fPC curve
Frame number of the grasp snapshot
(a)
(b)
Original curve
Reconstructed Curve
Value of original curve
Value of the curve
(c)
(d)

Clustering grasping motion in score space

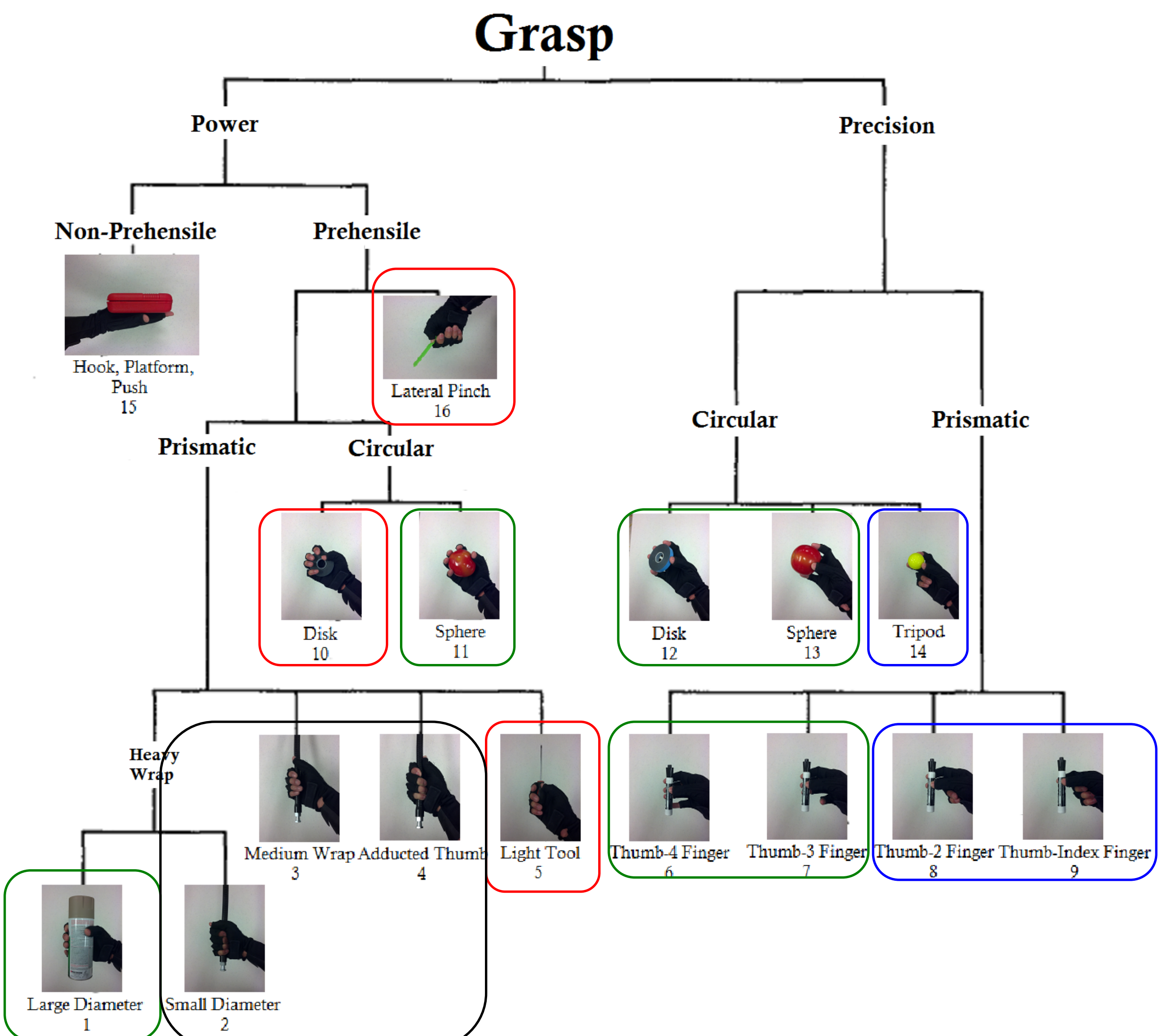


Data Driven Grasping Motion Taxonomy

- Stable across all subjects

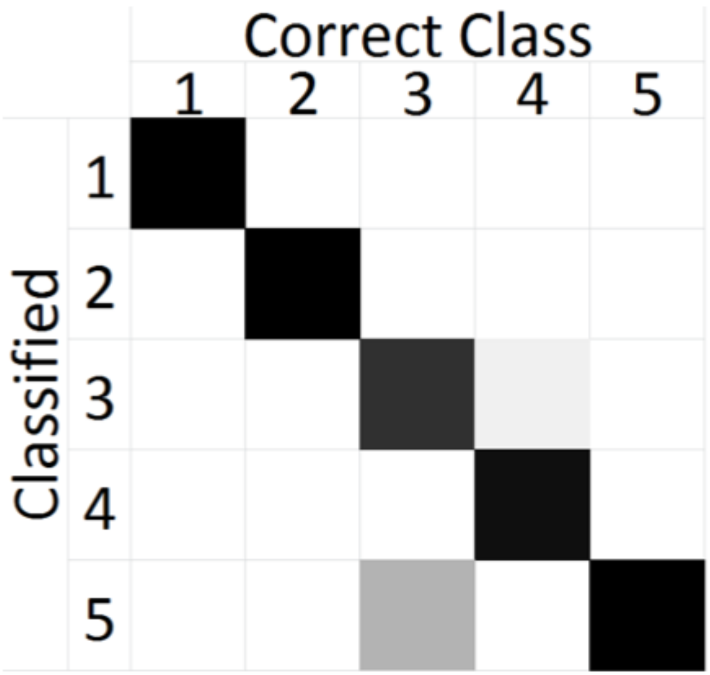


Compare with Cutkosky Taxonomy



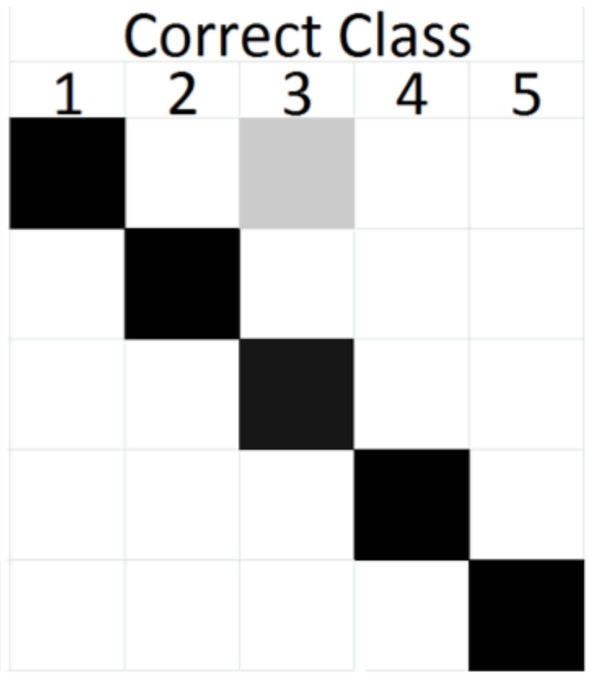
Evaluation

97%



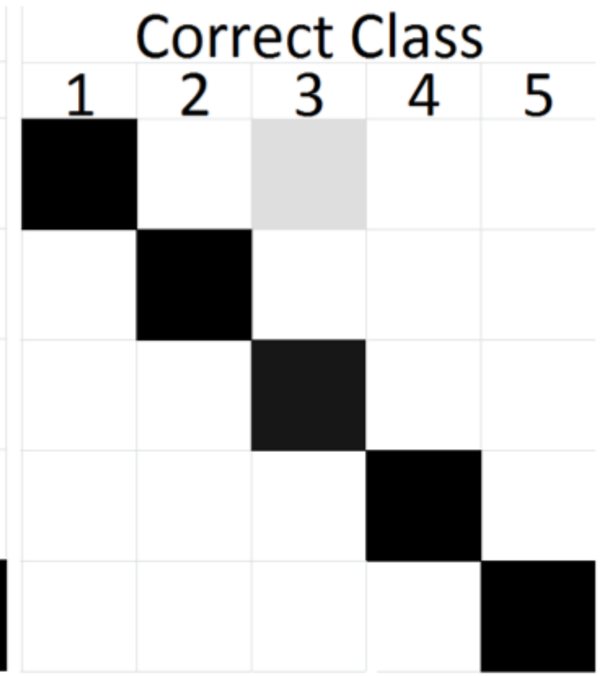
10-fold cross validation with all grasp types

89%



Leave one of the 15 Cutkosky grasp types for testing

99%



Use three of the five trials each grasp type for training

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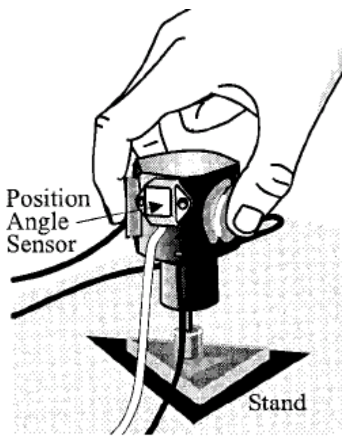
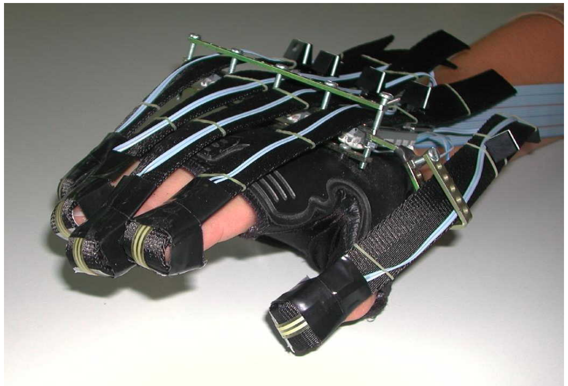
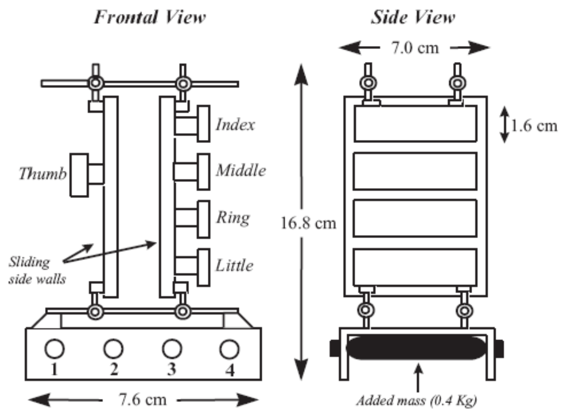
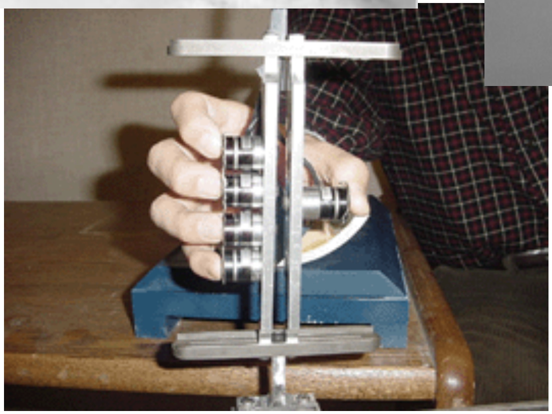
Measure Fingertip Force







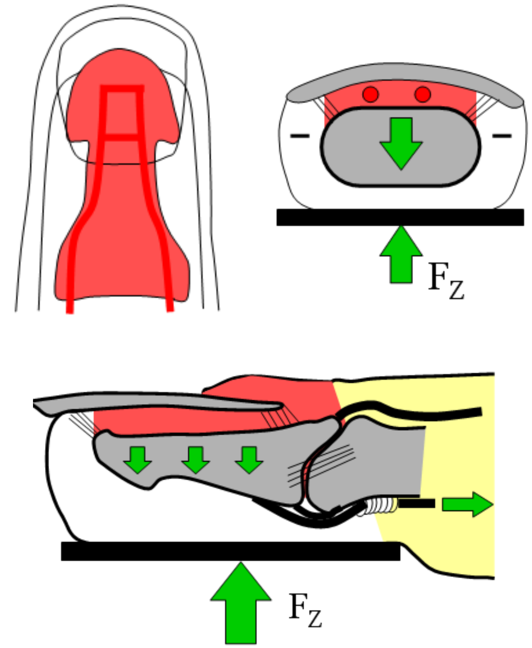


Problems

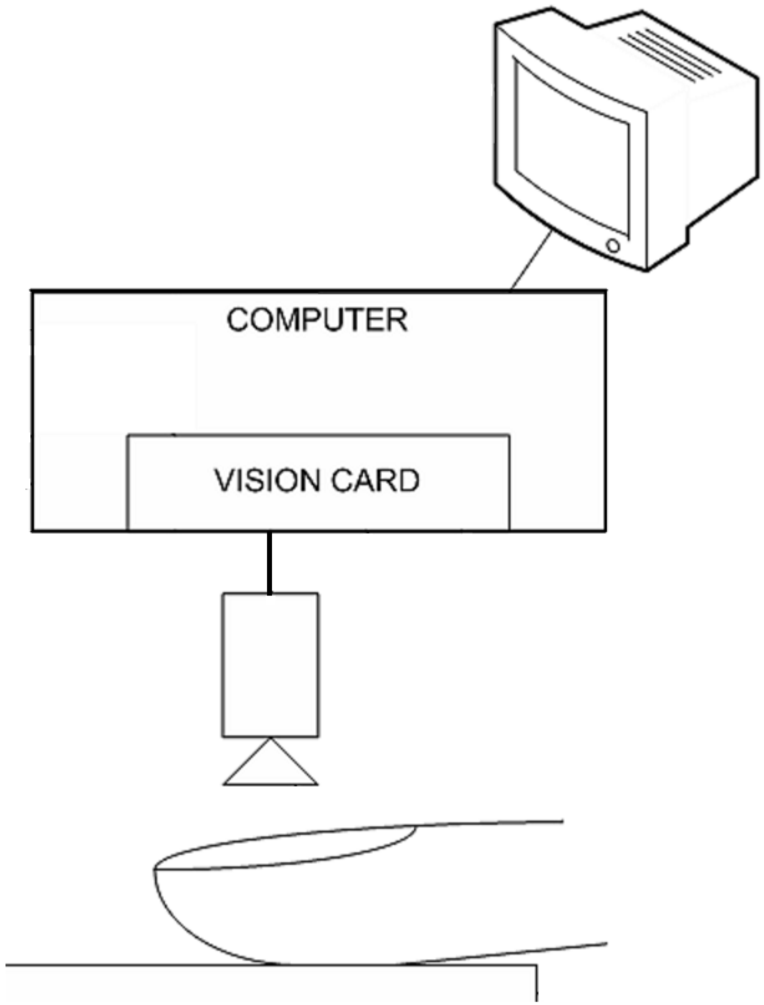
- Artifacts
  - predefined grasping points
  - fake surfaces
  - simple geometry
- Expensive
- Ideal grasping studies
  - everyday objects
  - contact points vary
  - distance, slope, and curvature vary
  - material type, and friction

Related Work

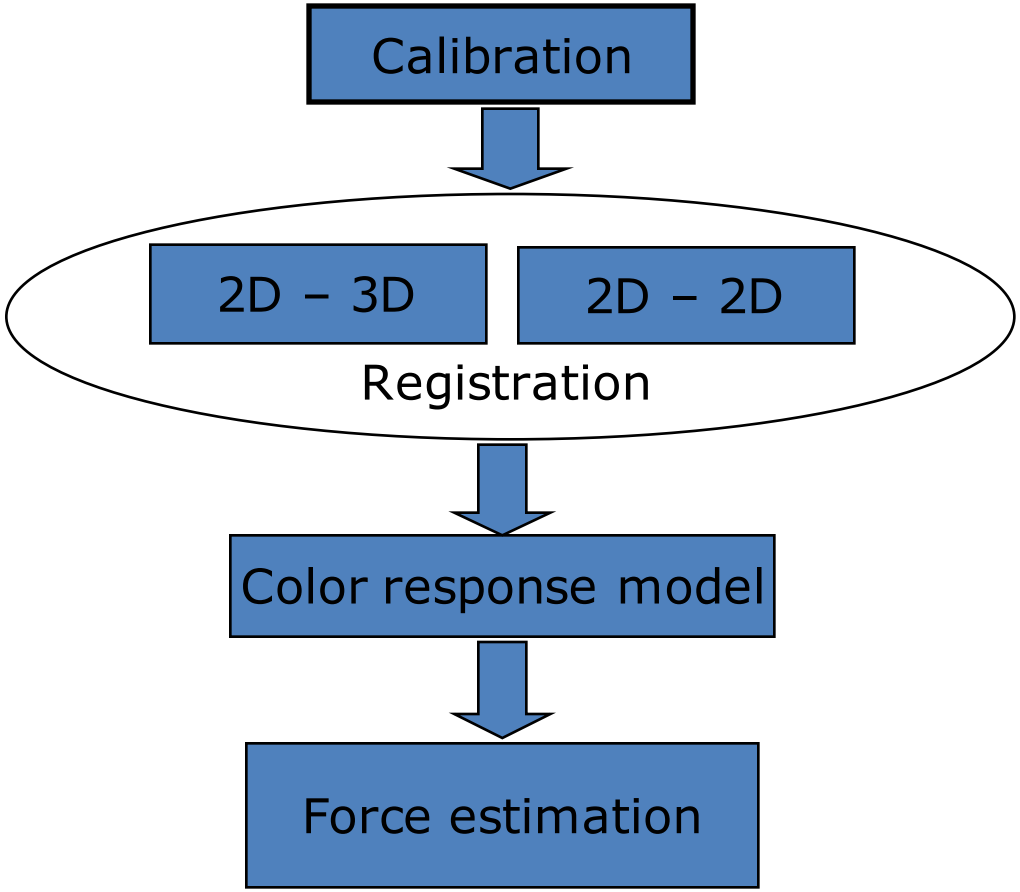
- Mascaro & Asada at MIT
- Infrared LEDs & Photodetectors
- Detect blood amount in arterioles
- Mounted on fingernails with transparent glue
- Advantages:
  - located on the nail
  - everyday objects
  - Natural contact surface
- New problems:
  - one sensor fits one fingernail
  - need individual calibration
  - 6 photo-detectors --Limited sampling
  - sample areas are pre-defined and not adjustable
  - small measurement range



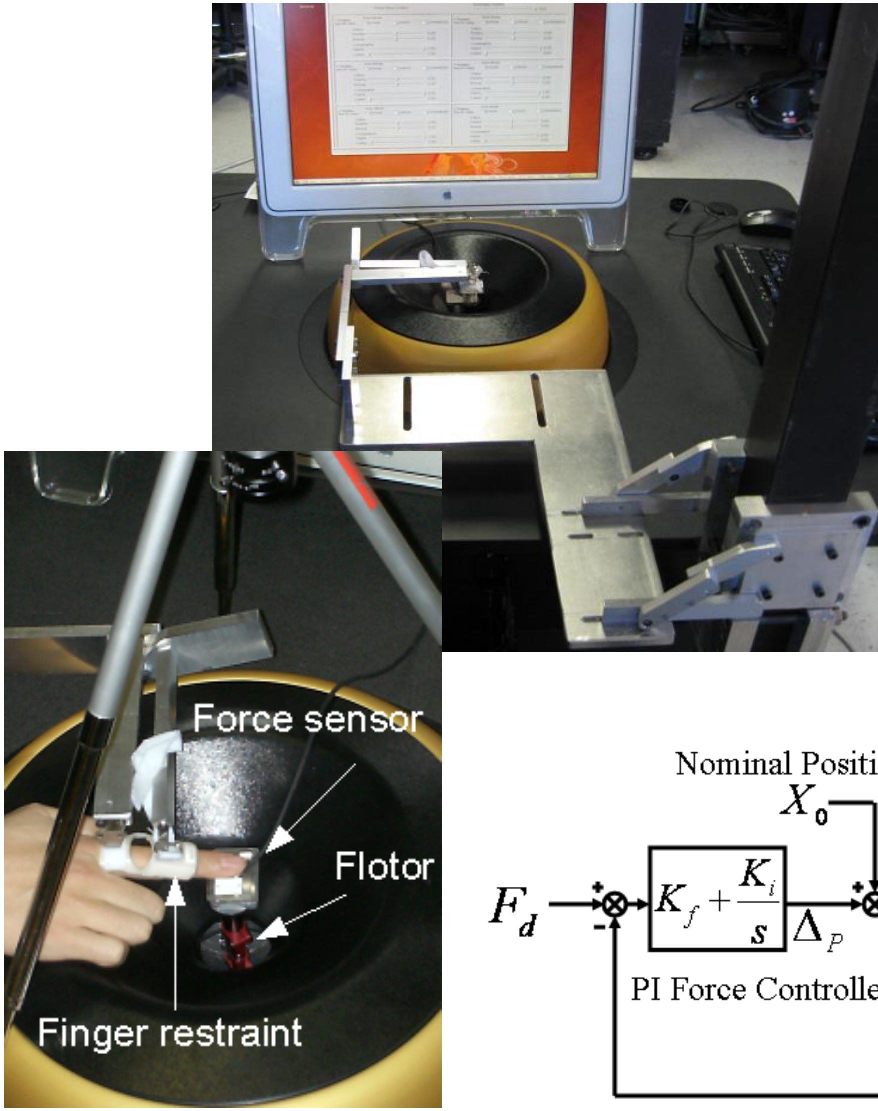
Computer Vision Approach

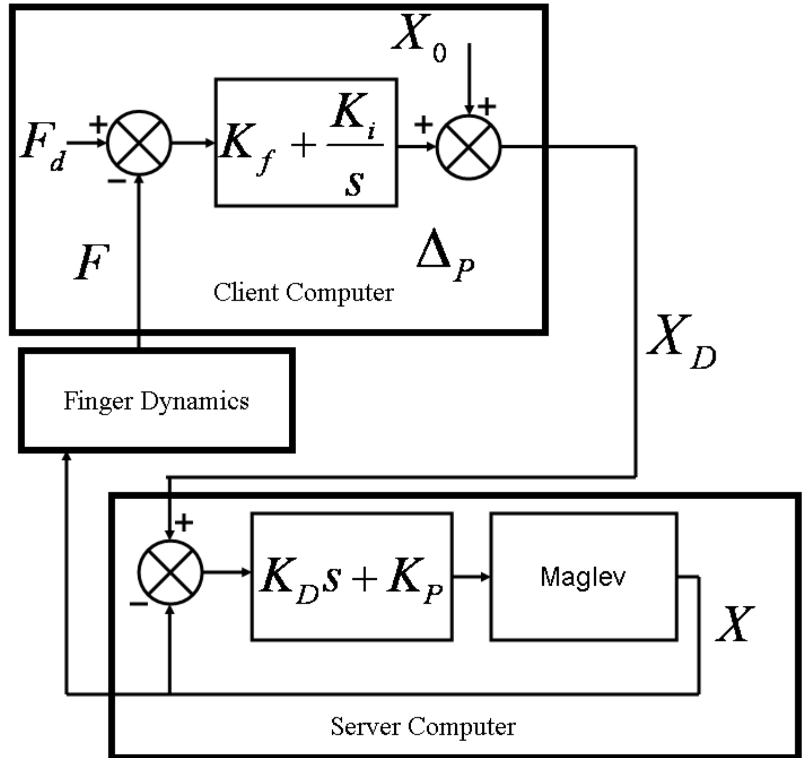


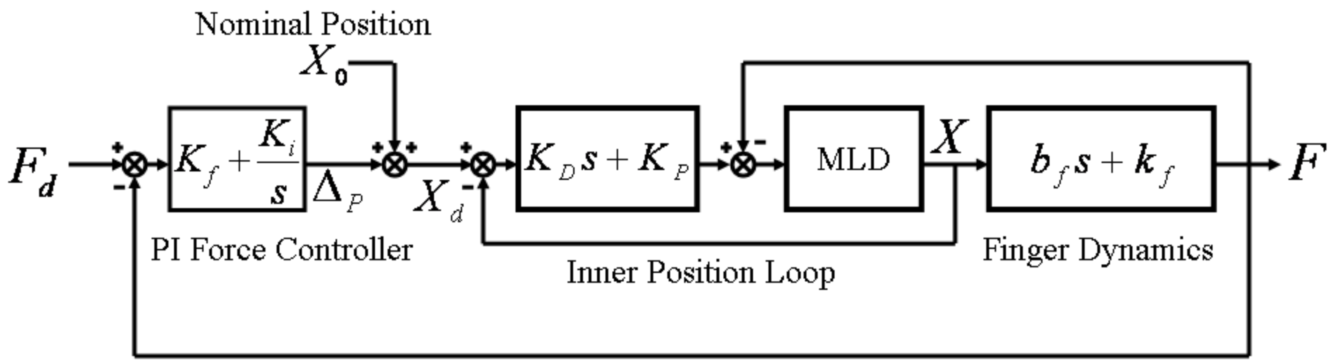
- Camera images the full back of the fingertip
- Natural lighting
- Computer vision techniques to interpret the color to force


Calibration
2D – 3D
2D – 2D
Registration
Color response model
Force estimation

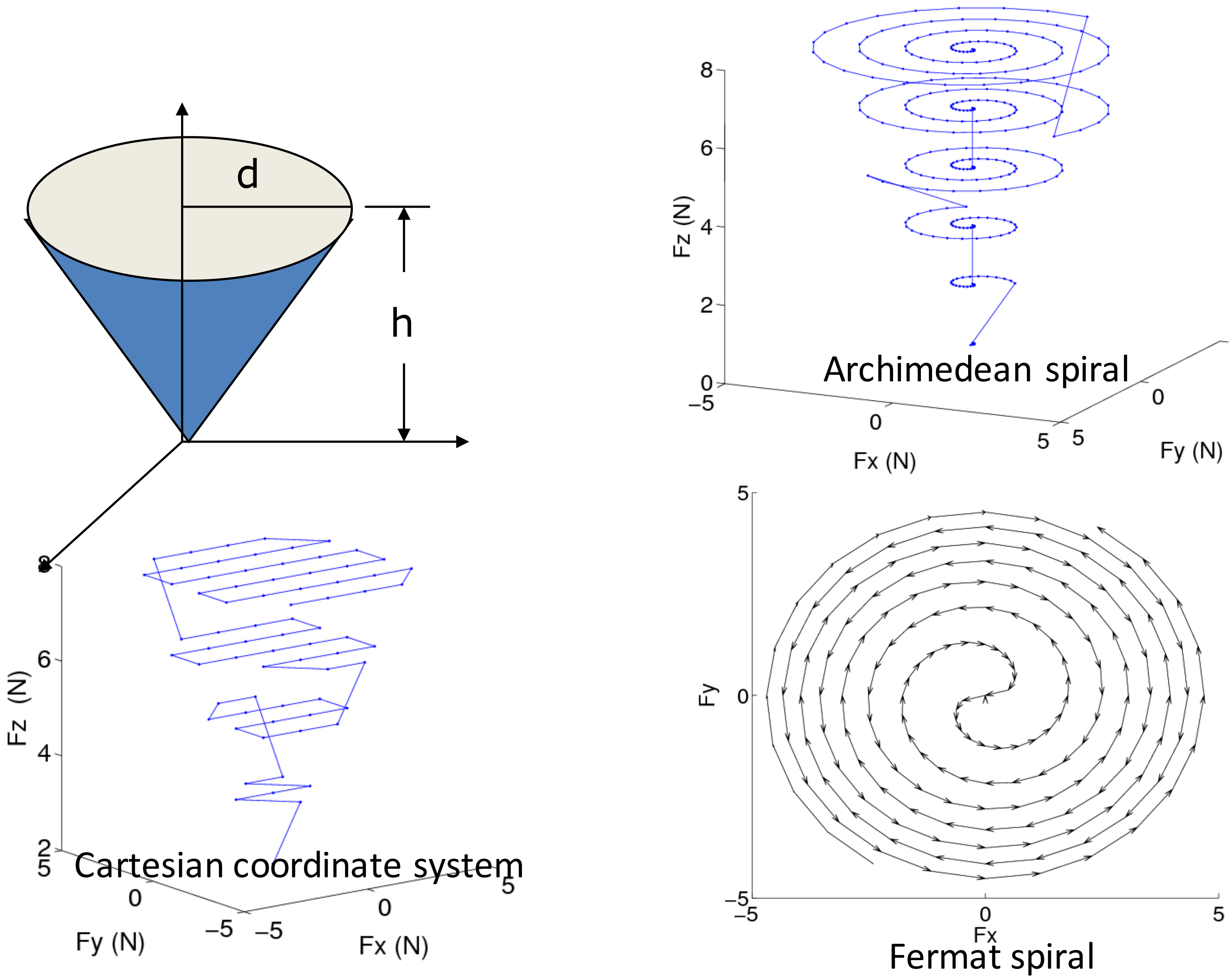
Automatic Calibration

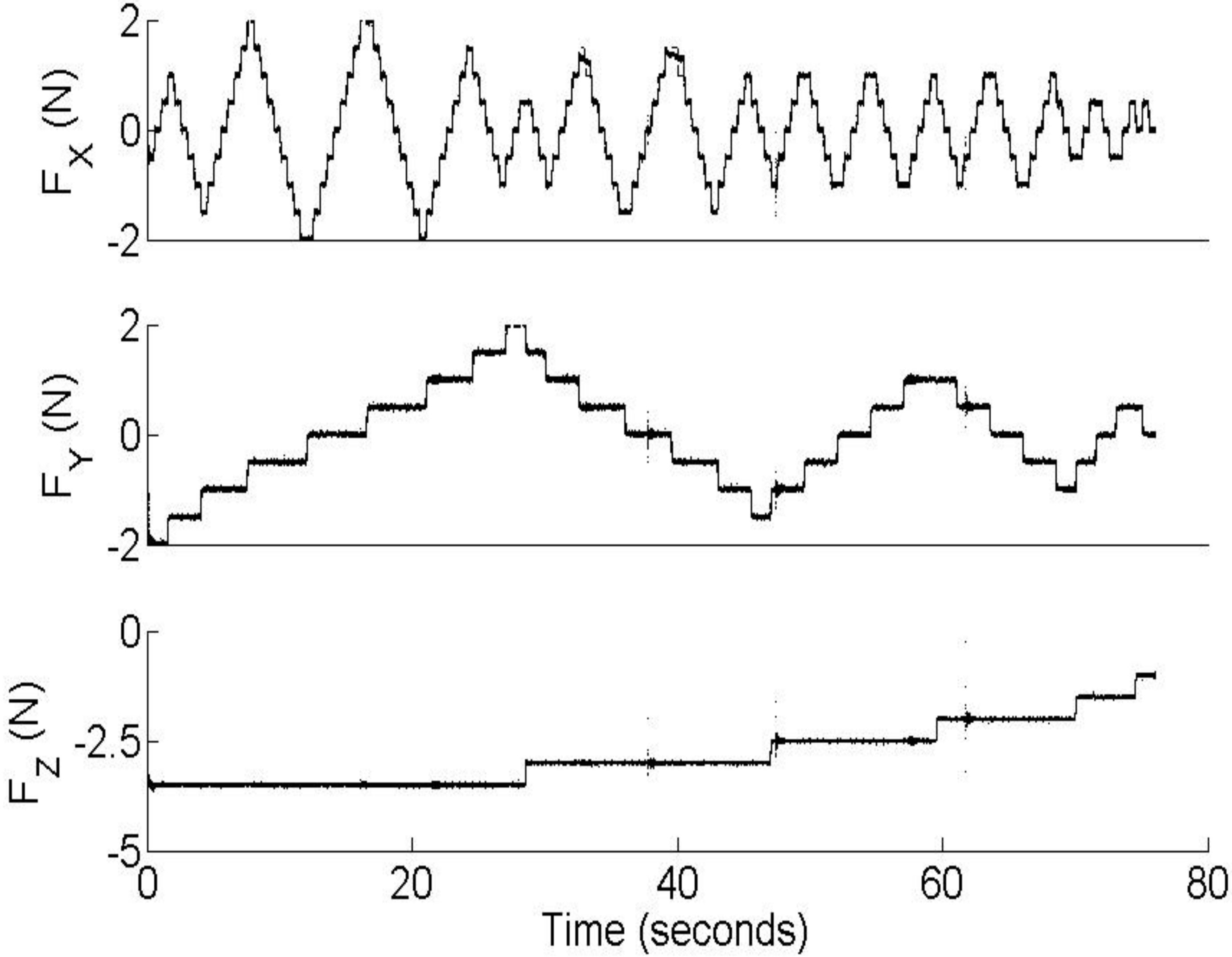






Force Trajectories

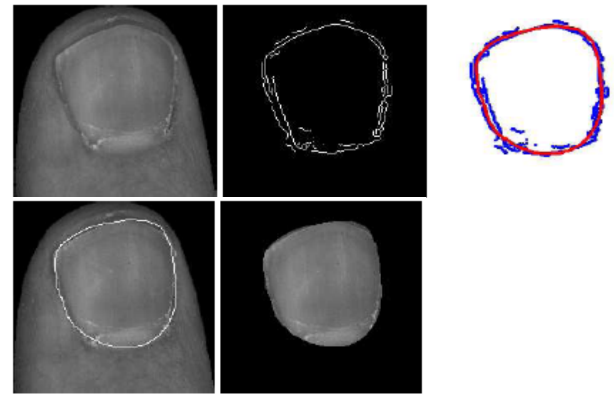




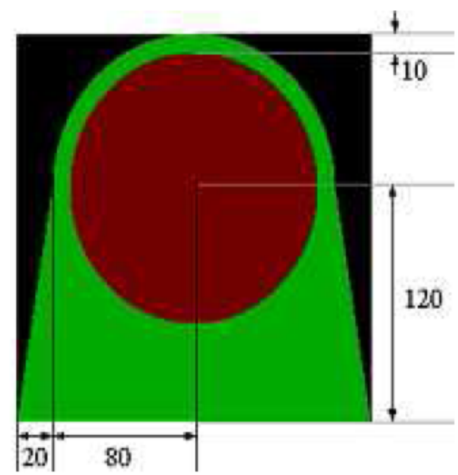
2
0
-2
F_X (N)
2
0
-2
F_Y (N)
0
-2.5
-5
F_Z (N)
0
20
40
60
80
Time (seconds)

2D Elastic Registration

- Images taken from different subjects
- Segment the nails
  - Canny edge filter
  - Cubic B-spline
- Elastically deform them to the same shape
  - Boundary -> boundary
  - Elastic sheets
  - Keeps relative location of the color pattern

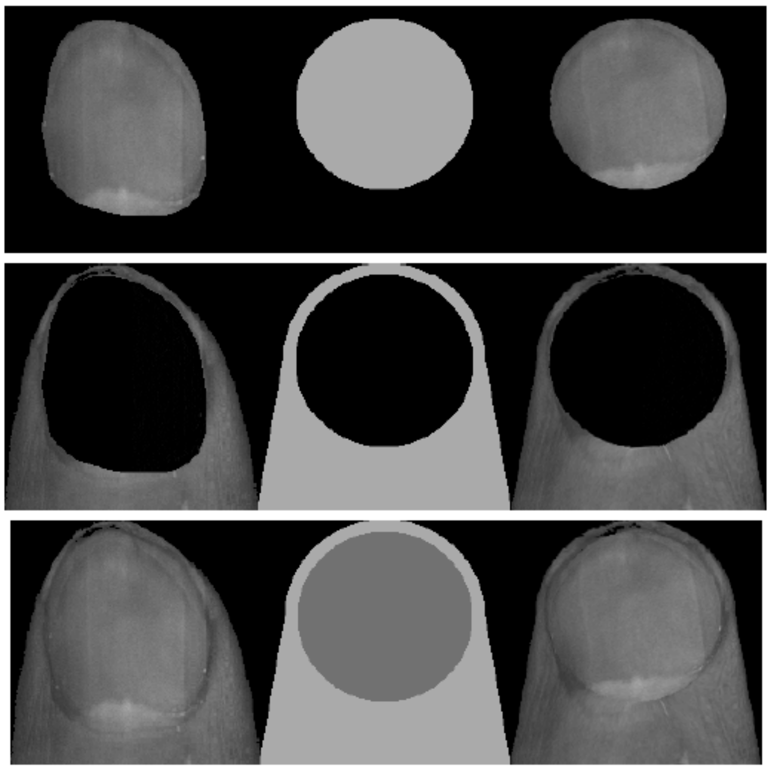


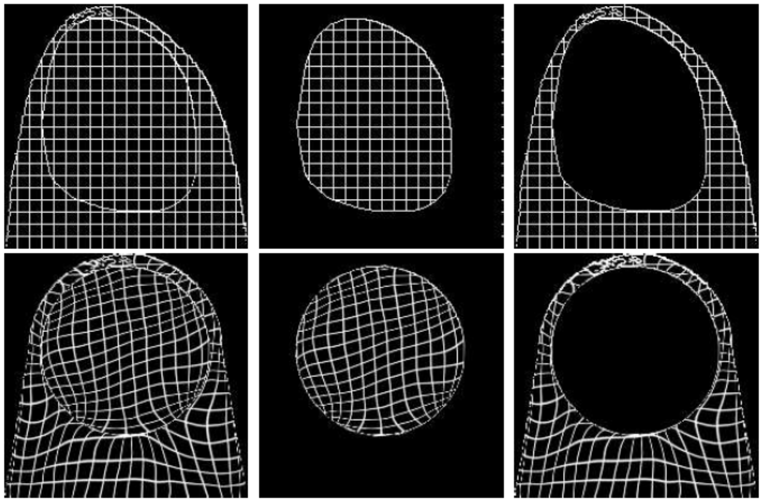
Segmentation

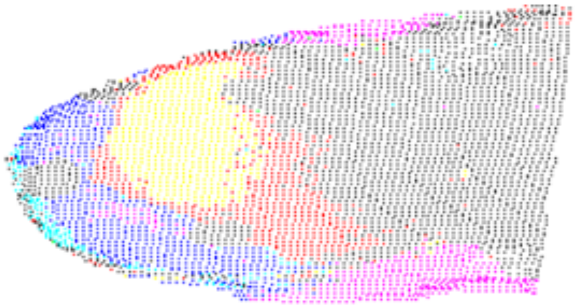


Standard shape

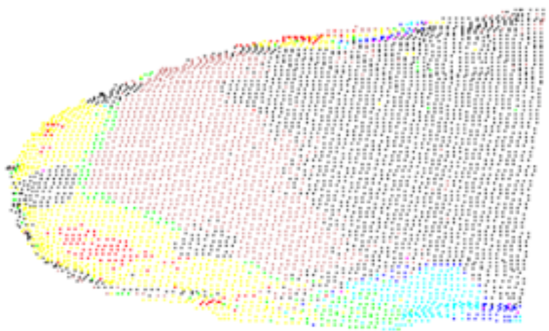
Deformation Mapping







Saturation Map

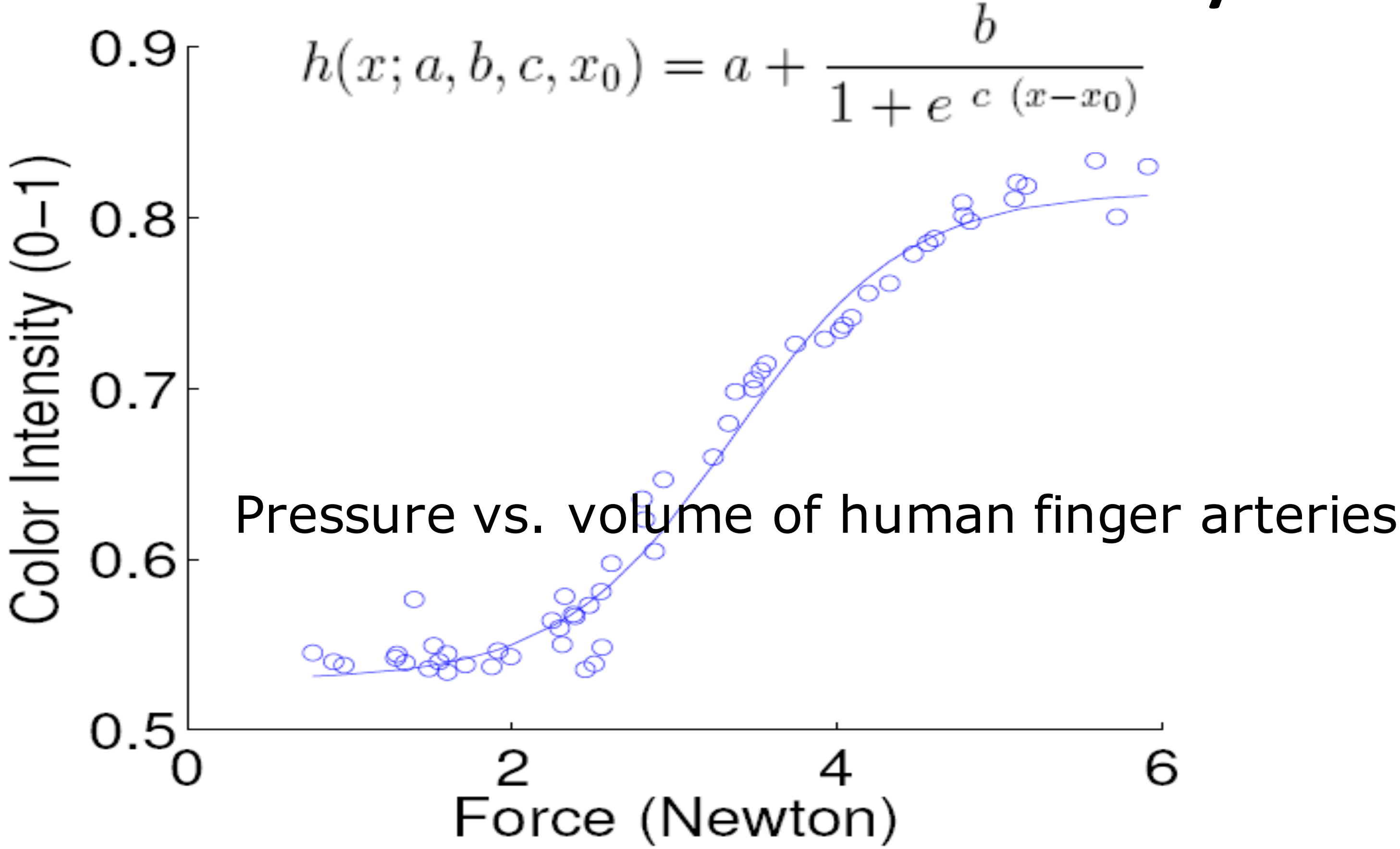


Start map
Green Channel

[0, 1) Dark Red
[1, 2) Red
[2, 3) Yellow
[3, 4) Green
[4, 5) Cyan
[5, 6) Blue
[6, 10) Magenta

- Points in the middle – start at 0–1 N, saturate at 2-3 N.
- Points in the front – start at 2-3 N, saturate at 5-6 N.
- Points on the skin – start at 4-5 N, saturate at 6-10N
- Surrounding skin transduces large force
- Combining all areas together gives big measurement range

Coloration Response Analysis



The color intensity changes from bright to dark with an increasing force

Modeling – Bayesian Prediction

- Force -> Color
- Color -> Force -- Inverse problem -> Bayesian inference model
- Combine all linear segments of the points together
- Optimal Bayesian Estimation – reduced to Weighted Least Squares

$$\hat{\mathrm{f}} = (\mathrm{B}'\Sigma^{-1}\mathrm{B})^{-1}\mathrm{B}'\Sigma^{-1}(\mathrm{h}-\mathrm{a})$$

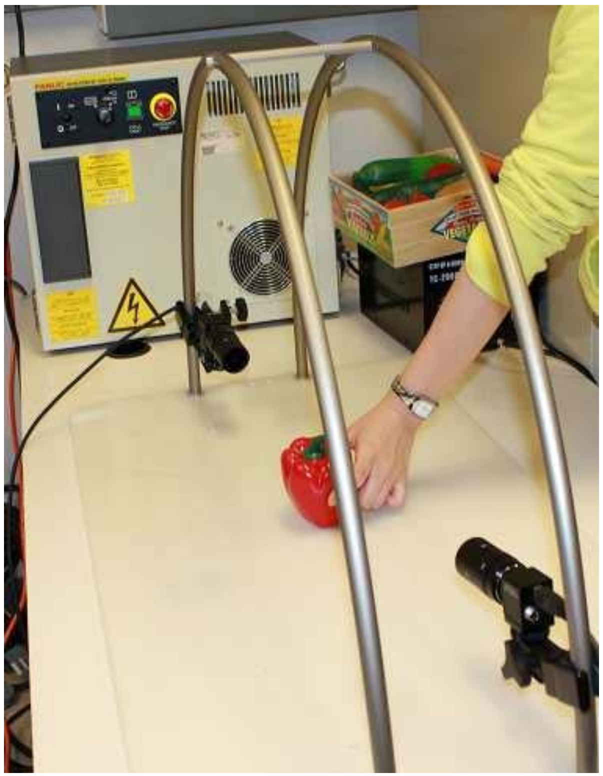
h – measured colors
Σ - covariance matrix of colors
B and **a** – regression parameters estimated with calibration

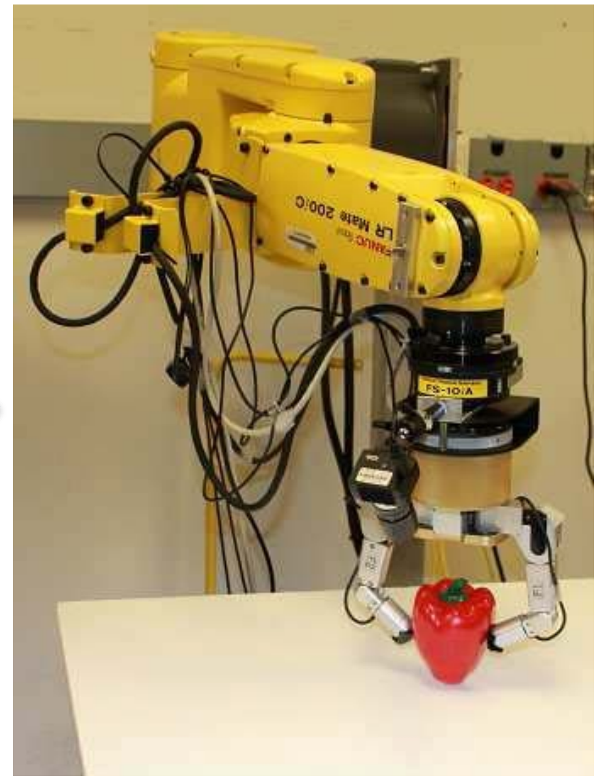
Individually trained

Verification Result

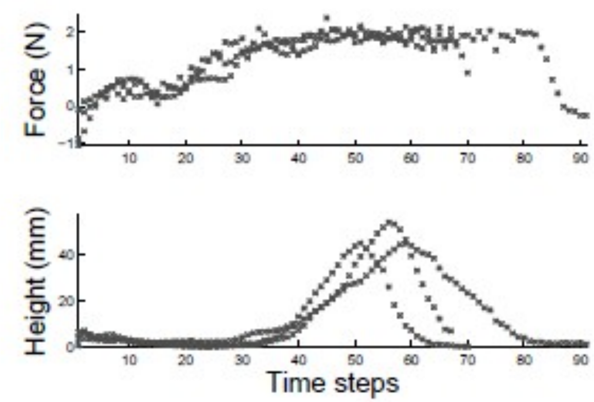
Subject	$+f_x$	$-f_x$	$+f_y$	$-f_y$	f_z
1	0.17	0.15	0.27	0.47	0.28
2	0.35	0.36	0.42	0.44	0.27
3	0.52	0.52	0.11	0.35	0.27
4	0.49	0.49	0.32	0.34	0.30
5	0.60	0.60	0.44	0.51	0.34
6	0.11	0.11	0.38	0.31	0.33
7	0.29	0.28	0.38	0.30	0.34

RMS errors (N) of estimation for force components for seven subjects

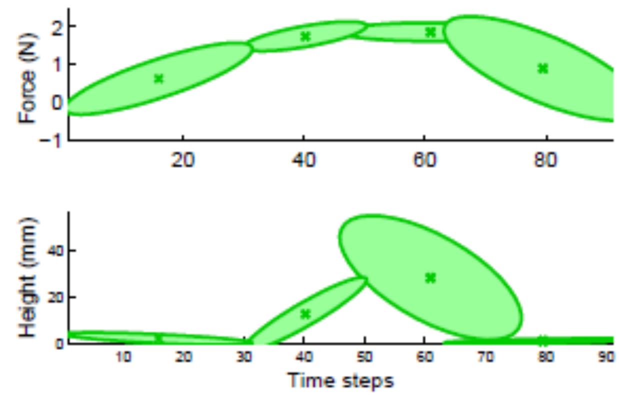




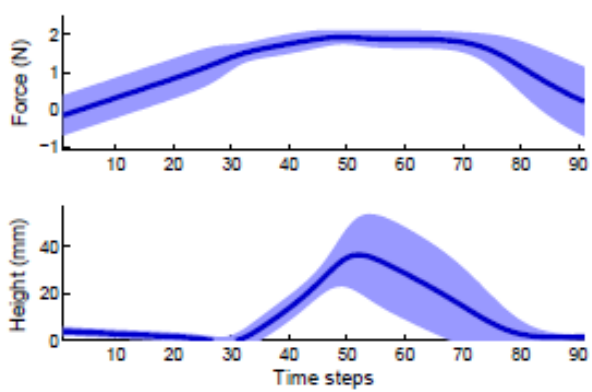
Learning and Execution Results of Motion and Force



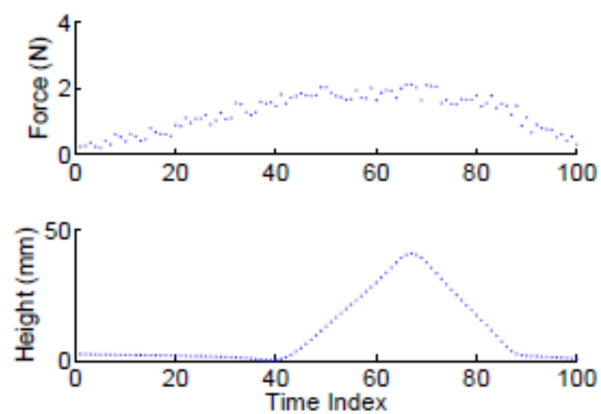
The demonstrated dataset



The GMM model result



Generated trajectory with GMR



Execution results by the robot

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- Learn grasping from human
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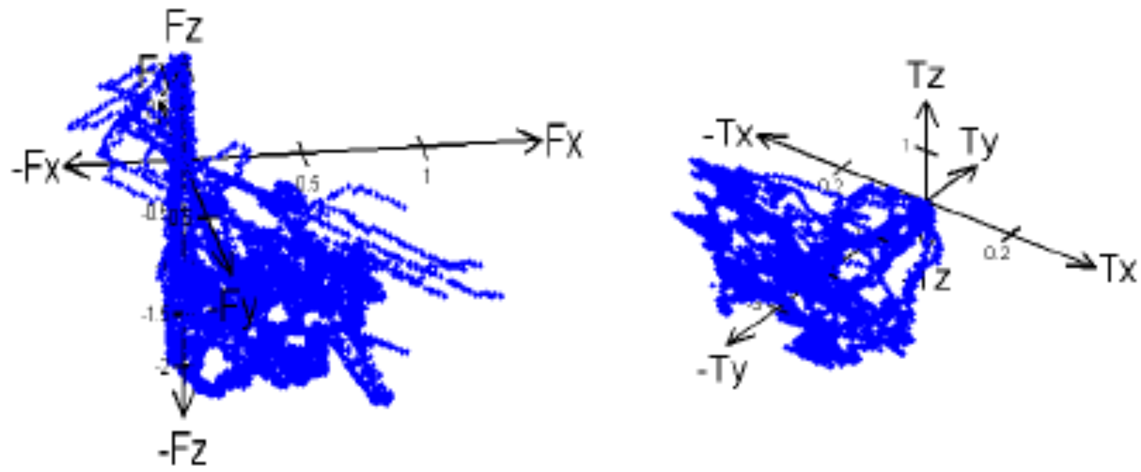
Grasping

- Grasping force feature on fingertip changes with not only objects but also the interaction in tasks
- Feature task wrench (force and torque interaction on the tool) space

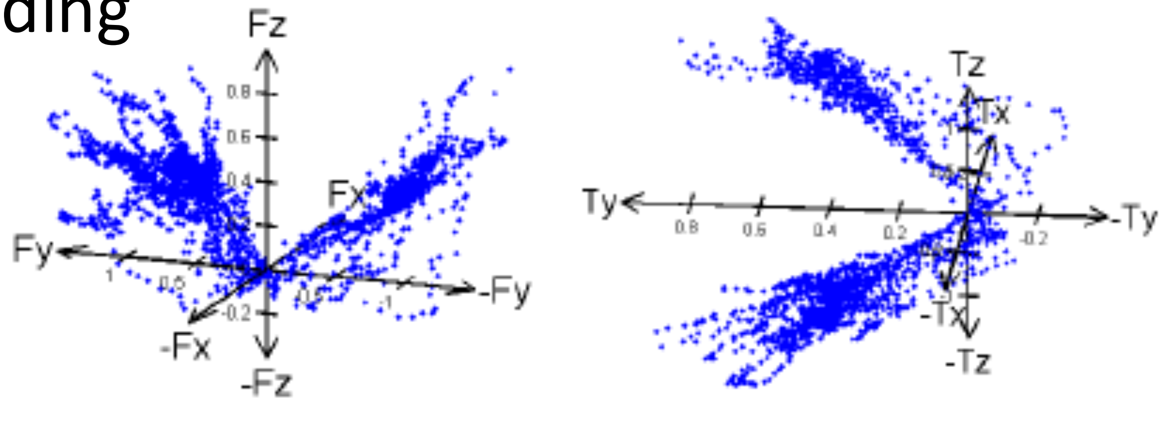
Use a Knife

Task 1: cutting



(a) (b)

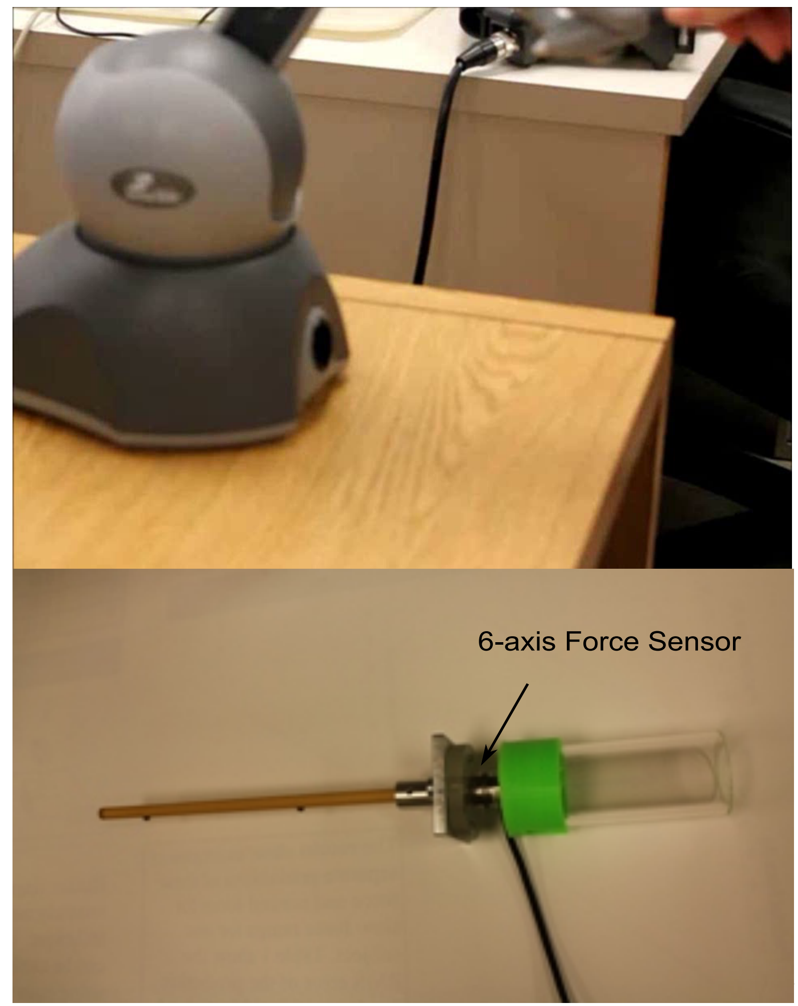
Task 2: butter spreading



(c) (d)

Measure a TWS Considering Task Disturbance Distribution

- Human demonstration a manipulation using a haptic device in virtual reality
- The external task-related disturbance was captured during the task execution
- The task disturbance data was down-sampled to build a non-parametric statistical distribution



Grasp Planning

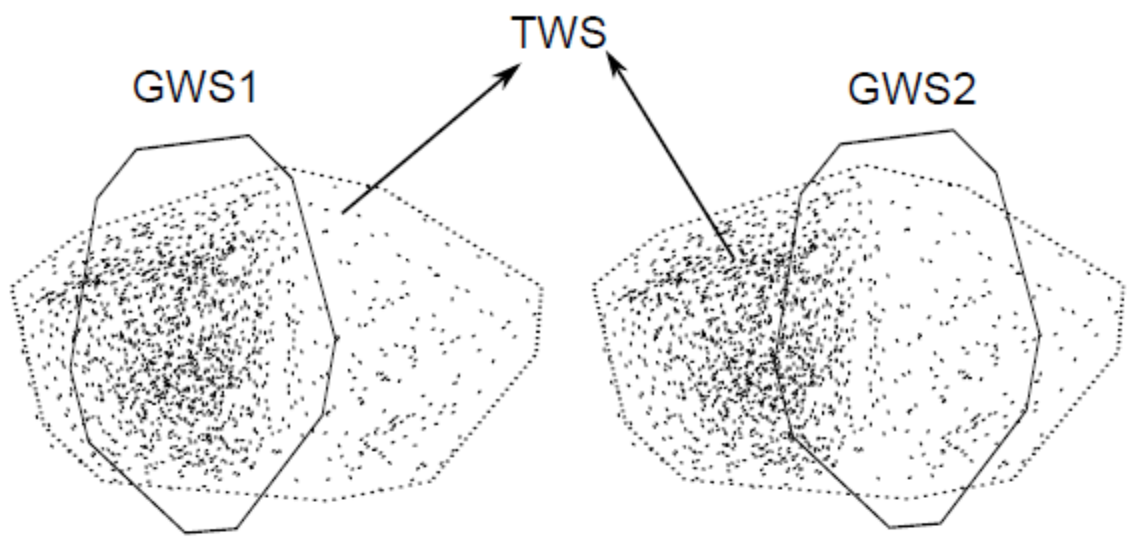
- Uses optimization mathematics to search for the optimal contact positions on an object
  - Cost function: grasp quality measures
- A typical grasp quality measure
  - Considers the ability of a grasp to resist the disturbance in a task

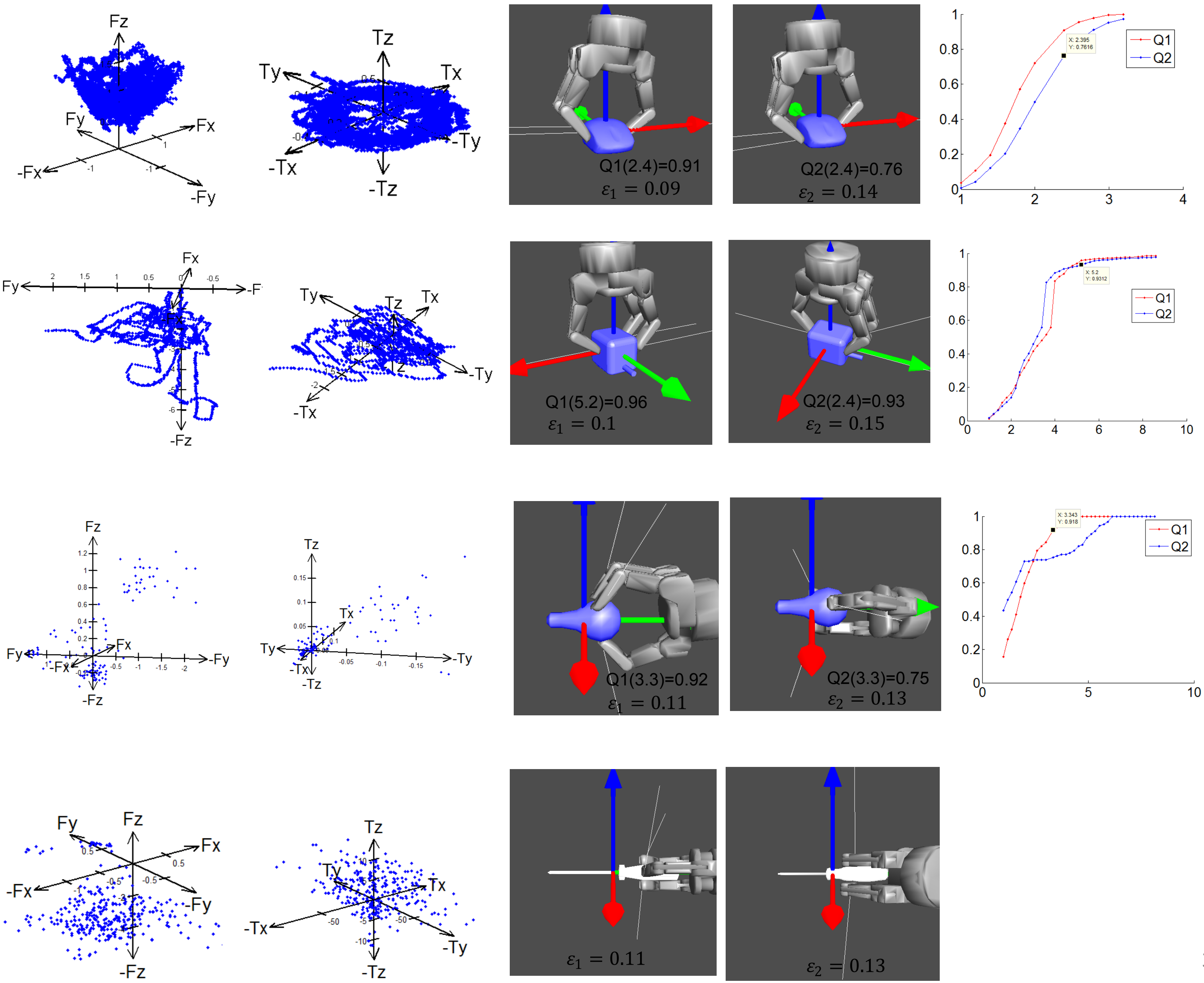
Quality Measure Base on Task Disturbance Distribution

- The quality measure k_m is no longer a reasonable constraint to the noisy TWS
- A new measure Q: measures the proportion TWS covers the scaled GWS by a factor of k

$$W = \{w(t) \mid w(t) \in TWS \cap w(t) \in k \bullet uGWS\}$$

$$Q(G) = \frac{|W|}{|TWS|}$$





Fz
Fx
Fy
-Fx
-Fy
Tz
Tx
Ty
-Tx
-Ty
-Tz
Q1(2.4)=0.91
$\varepsilon_1 = 0.09$
Q2(2.4)=0.76
$\varepsilon_2 = 0.14$
Q1
Q2
-Fz
Q1(5.2)=0.96
$\varepsilon_1 = 0.1$
Q2(2.4)=0.93
$\varepsilon_2 = 0.15$
Q1(3.3)=0.92
$\varepsilon_1 = 0.11$
Q2(3.3)=0.75
$\varepsilon_2 = 0.13$
$\varepsilon_1 = 0.11$
$\varepsilon_2 = 0.13$

Results

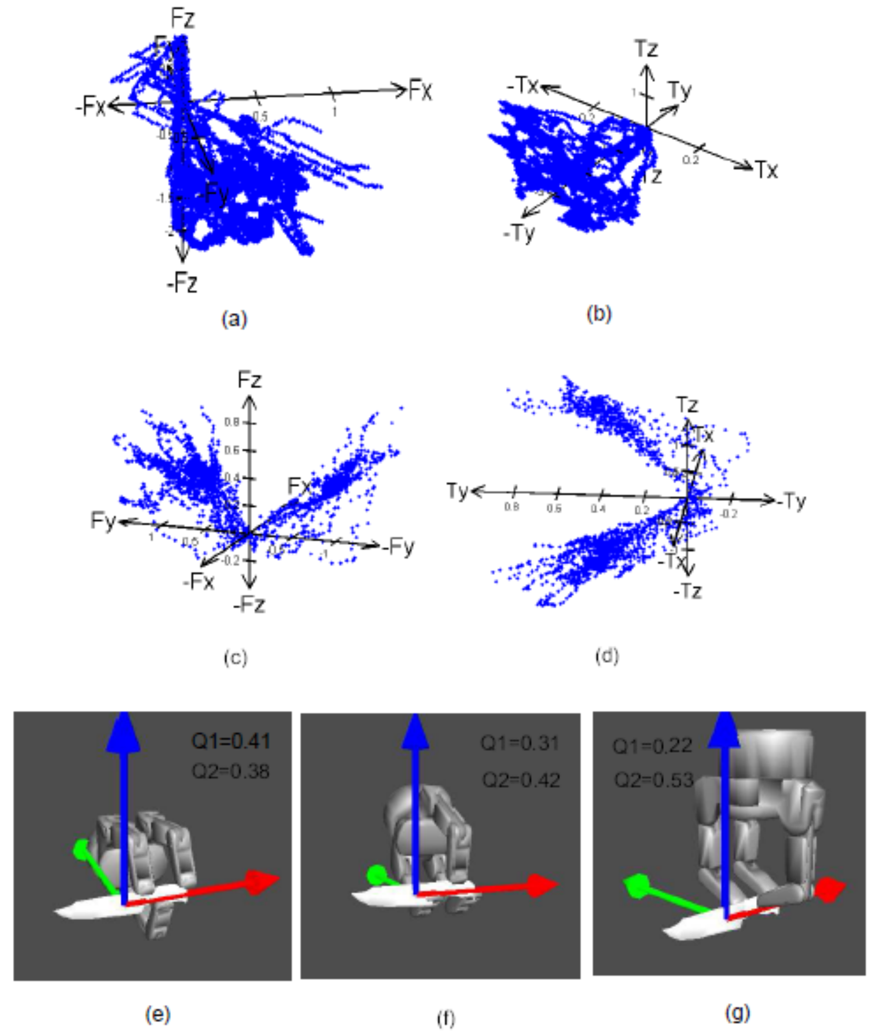
Example 2: kitchen knife.

- Task 1: cutting

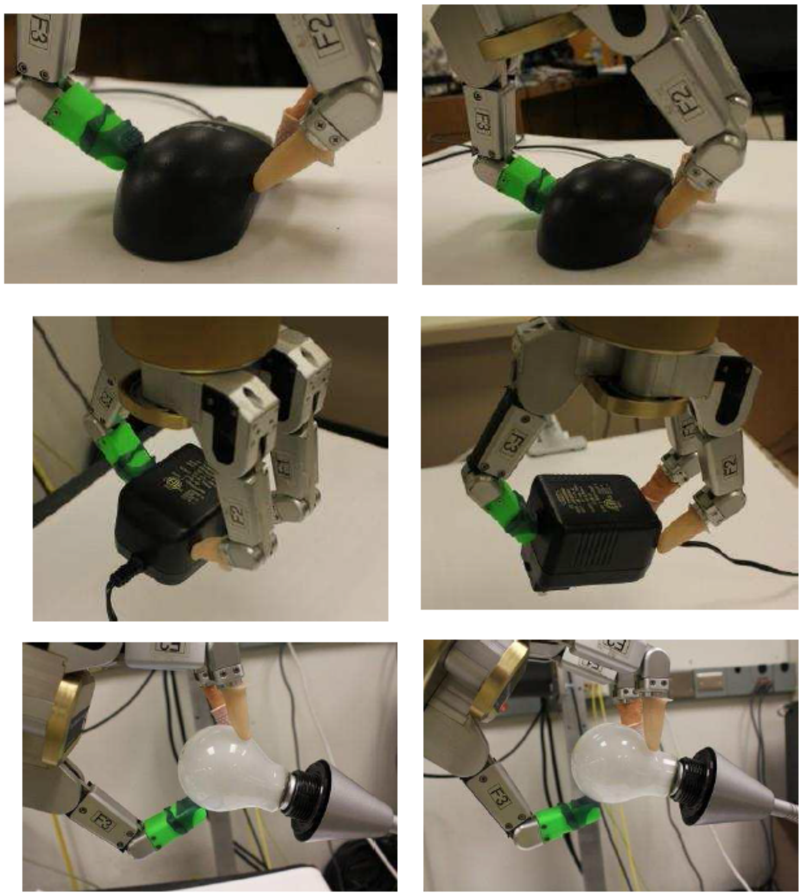
  K=8.04

- Task 2: butter spreading

  K=3.25



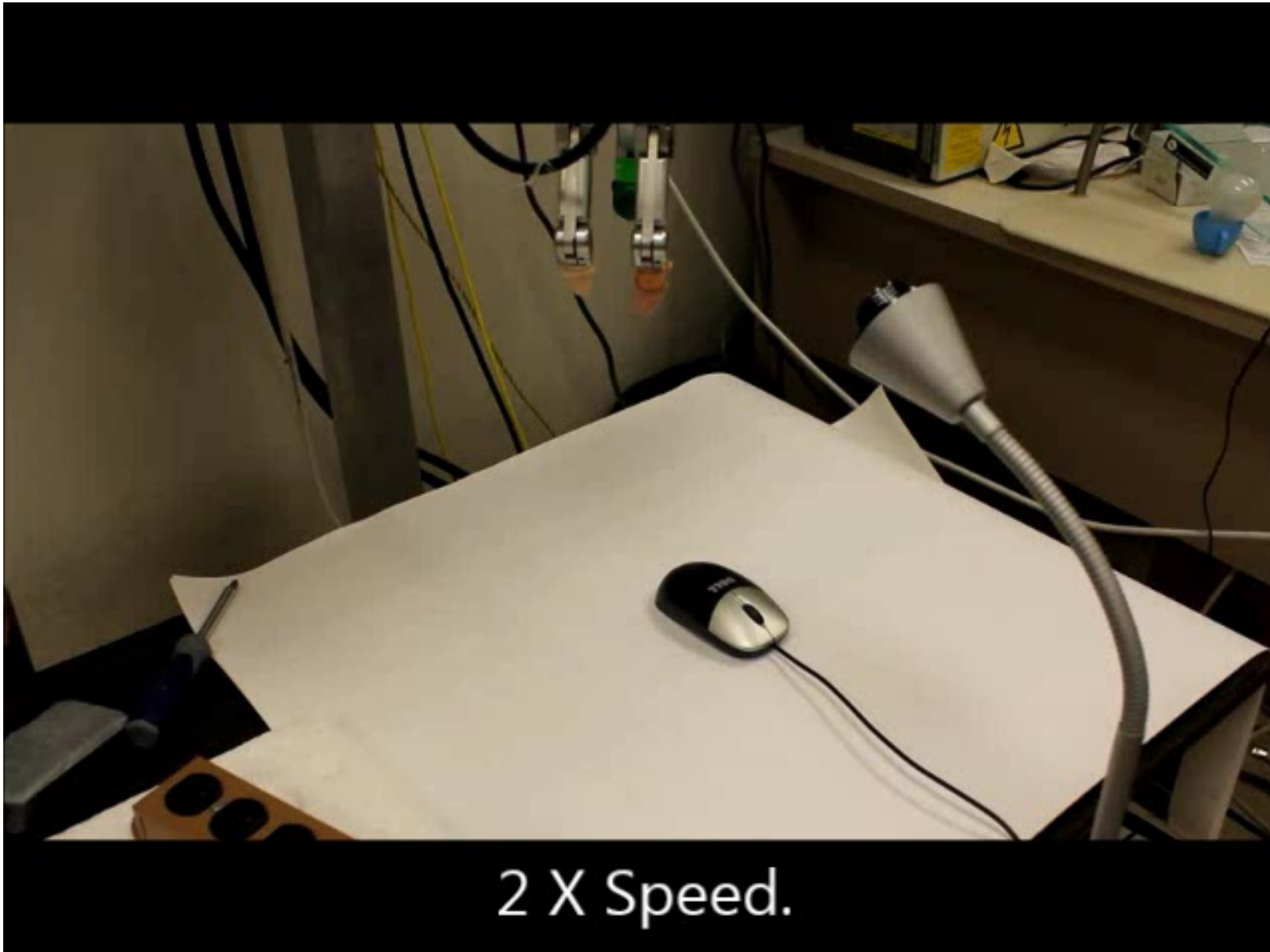
Success Rate of Real Execution



Our approach Force-closure approach

Table 1: Comparison of the success rate between the prospposed approach using task disturbance with non-task-oriented approach.

Task	Success Rate of Task Disturbance Based Grasp Planning	Success Rate of non-task oriented Grasp Planning
Task 1	60%	40%
Task 2	80%	70%
Task 3	70%	20%
Overall	70%	43.3%


2 X Speed.

References

1. Lin, Y. and Sun, Y., 2016. Task-oriented grasp planning based on disturbance distribution. In Robotics Research (pp. 577-592). Springer International Publishing.
2. Sun, Y., Yun Lin, and Yongqiang Huang (2016) Robotic Grasping for Instrument Manipulations, URAI, 1-3
3. Paulius, D. Huang, Y., Milton, R., Buchanan, W.D., Sam J., and Sun, Y. (2016) Functional Object-Oriented Network for Manipulation Learning, IROS, 3655-3662
4. Huang, Y. and Sun, Y. (2015) Generating Manipulation Trajectories Using Motion Harmonics, IROS, 4949-4954.
5. Lin, Y. and Sun, Y. (2015) Task-Based Grasp Quality Measures for Grasp Synthesis, IROS, 485-490.
6. Lin, Y. and Sun, Y., (2015) Grasp Planning to Maximize Task Coverage, Intl. Journal of Robotics Research, 34(9): 1195-1210.
7. Lin, Y., and Sun, Y. (2015) Robot Grasp Planning Based on Demonstrated Grasp Strategies, Intl. Journal of Robotics Research, 34(1): 26-42.
8. Sun, Y., and Y. Lin. Modeling Paired Objects and Their Interaction." In New Development in Robot Vision, pp. 73-87. Springer Berlin Heidelberg, 2015.
9. Sun, Y., Ren, S., and Lin, Y. (2014) Object-Object Interaction Affordance Learning, Robotics and Autonomous Systems, 62(4), 487-496
10. Lin, Y., Sun, Y. (2014) Grasp Planning Based on Grasp Strategy Extraction from Demonstration, IROS, pp. 4458-4463.
11. Dai, W., Sun, Y., Qian, X., (2013) Functional Analysis of Grasping Motion, IROS, pp. 3507-3513.
12. Christine Bringes, Yun Lin, Yu Sun, Redwan Alqasemi (2013) Determining the Benefit of Human Input in Human-in-the-Loop Robotic Systems, IEEE ROMAN 2013, pp. 1-8.
13. Ren S., Sun Y. (2013) Human-Object-Object-Interaction Affordance, IEEE Workshop in Robot Vision (WoRV)/Winter Vision Meeting (WVM), pp. 1-6, 2013
14. Lin Y., Sun Y. (2013) Grasp Mapping Using Locality Preserving Projections and KNN Regression, IEEE Intl. Conference on Robotics and Automation, pp 1068-1073
15. Lin Y., Ren S., Clevenger M., and Sun Y. (2012) Learning Grasping Force from Demonstration, IEEE Intl. Conference on Robotics and Automation, pp. 1526-1531.
16. Lin Y, Sun Y (2011) 5-D Force Control System for Fingernail Imaging Calibration, IEEE Intl. Conference on Robotics and Automation, pp. 1374-1379
17. Sun Y (2011) Fingertip Force and Contact Position and Orientation Sensor, IEEE Intl. Conference on Robotics and Automation, pp. 1114-1119