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

- PIP Joints
- MP Joints
- Sensor #
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

Raw data

Aligned data

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%)

Value of fPC curve

Frame number of the grasp snapshot

(a)

fPC 2 (19.8291%)

Value of fPC curve

Frame number of the grasp snapshot

(b)

Original curve

Value of original curve

Frame number of the grasp snapshot

(c)

Reconstructed Curve

Value of the curve

Frame number of the grasp snapshot

(d)
Clustering grasping motion in score space

- Large Diameter
- Small Diameter
- Medium Wrap
- Adducted Thumb
- Light Tool
- Thumb-4Finger
- Thumb-3Finger
- Thumb-2Finger
- Thumb-Index
- Power Disk
- Power Sphere
- Precision Disk
- Tripod
- Platform
- Lateral Pinch
Data Driven Grasping Motion Taxonomy

• Stable across all subjects
Compare with Cutkosky Taxonomy
Evaluation

10-fold cross validation with all grasp types

Leave one of the 15 Cutkosky grasp types for testing

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

Registration

2D – 3D

2D – 2D

Color response model

Force estimation
Automatic Calibration
Force Trajectories

Cartesian coordinate system

Archimedean spiral

Fermat spiral
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
Deformation Mapping
• 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

\[ h(x; a, b, c, x_0) = a + \frac{b}{1 + e^{c(x-x_0)}} \]

Pressure vs. volume of human finger arteries

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

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

- \(h\) – measured colors
- \(\Sigma\) - covariance matrix of colors
- \(B\) and \(a\) – regression parameters estimated with calibration

Individually trained
Verification Result

<table>
<thead>
<tr>
<th>Subject</th>
<th>$+f_x$</th>
<th>$-f_x$</th>
<th>$+f_y$</th>
<th>$-f_y$</th>
<th>$f_z$</th>
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<td>1</td>
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<td>0.27</td>
<td>0.47</td>
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<td>0.11</td>
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<td>0.51</td>
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<td>0.28</td>
<td>0.38</td>
<td>0.30</td>
<td>0.34</td>
</tr>
</tbody>
</table>

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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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

Task 2: butter spreading
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 $k$

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

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

Example 2: kitchen knife.

- Task 1: cutting
  \[ K=8.04 \]

- Task 2: butter spreading
  \[ K=3.25 \]
Success Rate of Real Execution

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

<table>
<thead>
<tr>
<th>Task</th>
<th>Success Rate of Task Disturbance Based Grasp Planning</th>
<th>Success Rate of non-task oriented Grasp Planning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task 1</td>
<td>60%</td>
<td>40%</td>
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<tr>
<td>Task 2</td>
<td>80%</td>
<td>70%</td>
</tr>
<tr>
<td>Task 3</td>
<td>70%</td>
<td>20%</td>
</tr>
<tr>
<td>Overall</td>
<td>70%</td>
<td>43.3%</td>
</tr>
</tbody>
</table>

Our approach  | Force-closure approach
2 X Speed.
References

2. Sun, Y., Yun Lin, and Yongqiang Huang (2016) Robotic Grasping for Instrument Manipulations, URAI, 1-3