MICROMANIPULATION USING VISION and FORCE FEEDBACK

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Dedicated to Bill Wolovich
Micromanipulation

- Manipulation of objects at
  - microscale
  - mesoscale
  with micron/submicron tolerances

Pollens (~ 40µm)  Glass Particle (~ 90µm)  Polymer Balls (~ 65 µm)  Polystyrene Balls (~ 450 µm)

Relative accuracy of 1 - 5%  →  0.5 – 2.5 µm
Micro Devices

Low-g Accelerometer

Hard Drive’s Read/Write Head

Digital Micromirror Device
Life Sciences and Medical Applications

Automated Tracking of Cell Populations

- measurements of a range of cell behaviors

  - migration (translocation),
  - mitosis (division),
  - apoptosis (death),
  - lineage (parent-daughter relations, e.g. Yeast model of ageing)

- valuable in medical research: genomics, proteomics, stem cell biology, and tissue engineering

293T Human Kidney Cells and Jurkat Cancer Cells
Challenges

– Autofocusing
– Calibration of the Optical System
– Robust Feature Extraction and Real-Time Tracking
– Robust Visual Servoing Algorithms
– 3D Reconstruction
– Force Estimation Using Image Data for Teleoperations
Autofocusing

Defocused and Focused Images of Drosophila

Defocused and Focused Images of Pumpkin Cells
Optical System Calibration

Parameters

Objective focal length, Tube Length, Magnification etc.

Projection Model

$$u(1 + k_1 r^2) = (T_{op} + f) \frac{r_{11} X_g + r_{12} Y_g + r_{13} Z_g + T_x}{r_{31} X_g + r_{32} Y_g + r_{33} Z_g + T_z}$$

$$v(1 + k_1 r^2) = (T_{op} + f) \frac{r_{21} X_g + r_{22} Y_g + r_{23} Z_g + T_y}{r_{31} X_g + r_{32} Y_g + r_{33} Z_g + T_z}$$

$$T_z \approx f + d$$

Nonlinear Optimization

ESTIMATED PARAMETERS
Reconstruction/Reprojection Errors

<table>
<thead>
<tr>
<th>Magnification</th>
<th>1.6</th>
<th>6.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Error (µm)</td>
<td>0.220</td>
<td>0.063</td>
</tr>
<tr>
<td>Max Error (µm)</td>
<td>1.720</td>
<td>0.584</td>
</tr>
</tbody>
</table>
3D View by Side Camera

- x-z (depth) information from the side camera
- x-y (sample stage) information from the optical microscope
A Novel Online Calibration Technique

\[
\begin{pmatrix}
x_{im} \\
z_{im}
\end{pmatrix} = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} \begin{pmatrix} x_w \\
z_w
\end{pmatrix} + \begin{pmatrix} q_1 \\
q_2
\end{pmatrix}
\]

\[
\begin{pmatrix}
x_{im} \\
y_{im} \\
z_{im}
\end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} x_w \\
y_w \\
z_w
\end{pmatrix} + \begin{pmatrix} t_x \\
t_y \\
t_z
\end{pmatrix}
\]

- adapted to different magnifications
- robust to noise
- high accuracy
- high convergence rate
Robust Feature Extraction

Top View of the Sample Stage

Image After Thresholding

Segmentation

Extracted Circles
Robust Feature Extraction

Image of the Probe

Edge Pixels of the Probe
Probe Tip Detection &
Real-Time Tracking

Tracking at video rate (30 fps)

Kalman Filtering &
Template Matching
Design of Visual Controllers

Having optical system parameters from calibration and real time image feature measurements from tracking, how do we implement vision based control algorithms to move the gripper?

**Optimal Control**

\[
E(k+1) = (f(k+1) - f^*(k+1))^T Q(f(k+1) - f^*(k+1)) + u^T(k)Lu(k)
\]

\[
u(k) = -(TJ^T(k)Q TJ(k) + L)^{-1}TJ^T(k)Q( f(k) - f^*(k+1))
\]
Micropositioning Results

<table>
<thead>
<tr>
<th>Step (pixels)</th>
<th>ts (sec)</th>
<th>Acc. (µm)</th>
<th>Prec. (µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1x</td>
<td>50</td>
<td>0.8</td>
<td>9.86</td>
</tr>
<tr>
<td>4x</td>
<td>50</td>
<td>0.45</td>
<td>1.35</td>
</tr>
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</table>
Trajectory Tracking Results

![Image of microgripper and trajectory]

**Results of trajectory tracking for calibrated visual servoing**

<table>
<thead>
<tr>
<th></th>
<th>Square</th>
<th>Circular</th>
<th>Sinusoidal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acc. (µm)</td>
<td>Prec. (µm)</td>
<td>Acc. (µm)</td>
<td>Prec. (µm)</td>
</tr>
<tr>
<td>1x</td>
<td>5.93</td>
<td>2.28</td>
<td>7.72</td>
</tr>
<tr>
<td>4x</td>
<td>1.47</td>
<td>1.19</td>
<td>1.57</td>
</tr>
</tbody>
</table>
Automatic Manipulation by Pushing

Mode 0. Explore
- Target Pose
- Probe Tip Detection
- Object (Ball) Detection
- Which Ball to Manipulate
- Tracking using Kalman Filters

Mode 1. Obstacle Avoidance

Mode 2. Automated Pushing
- Visual Servoing

Mode 3. Home
Obstacle Avoidance
Active 3D Reconstruction

• Shape from Focus

2D Images ➔ 3D Model

• 2D Images at different focus levels captured to create 3D model of AFM Probe
Passive 3D Reconstruction

Shape From Defocus

- estimating the 3D surface of a scene from a set of two or more images of the scene
- exploiting defocus to recover the depth
Force Sensing

- In order to achieve high dexterity in manipulation, control of the interaction forces is required.

- In micro-manipulation, control of interaction forces necessitates force sensing in mili-Newton range with nano-Newton resolution.
Force Estimation and Mechanical Characterization

\[ F = m\ddot{x} + b\dot{x} + k_1x + k_2x^3 \implies F_i = \begin{pmatrix} \dddot{x}_i \\ \dot{x}_i \\ x_i \\ x_i^3 \end{pmatrix} \Phi_i^T \begin{pmatrix} m \\ b \\ k_1 \\ k_2 \end{pmatrix} \theta \]

\[ \hat{\theta} = \arg \min (\| F - \Phi \theta \|^2 + \delta \| \theta \|^2 ) = (\Phi^T \Phi + \delta I)^{-1} \Phi^T F \]
Applications

- Automated injection
  - intracytoplasmic sperm injection (ICSI), DNA injection, gene therapy
  - manual injection
    - low success rate and poor reproducibility
  - efficiency of injection can be improved by using visual feedback
Summary

- Robust and repeatable algorithms for optical system calibration
- Robust feature extraction and real-time tracking
- Path Planning, Visual servoing, Automatic Manipulation by Pulling
- 3D Reconstruction from Focus and Defocus
- Force Estimation and Mechanical Characterization
THANK YOU

&

BEST WISHES, BILL!