Automated Micro Robotic Manipulation using Optical Tweezers

Ashis G. Banerjee, Ph.D.
Assistant Professor
Department of Industrial & Systems Engineering
Department of Mechanical Engineering
University of Washington, Seattle, WA
Optical Tweezers as Micro Robots

Infra-red fiber laser source

Spatial light modulator (SLM) to create multiple optical (laser) traps with independent control over trap positions in 3D

Lamp (Light source)

Specimen

Motorized stage

Objective (End effector)

Diffraction grating (Actuator)

Telescope

Mirror

Camera (Sensor)

Laser Source (Base of manipulator)
### Advantages

- Multiplexing capability (up to 100 objects concurrently)
- Precise and independent control over each object in 3D
- Flexibility in choice of manipulated object (particles, cells, biomolecules, etc.) and medium
- Easy to release trapped objects after manipulation
- Minimal object damage during manipulation
Automated Manipulation

• Motivation
  – Manipulate large number of objects in parallel
  – Reliable and efficient manipulation

• Challenges
  – Stochastic and non-linear system dynamics
  – Uncertainty in sensing (optical imaging) measurements
  – Fast motion control updates at rates of several Hz
  – Optimized manipulator design (number, positions, and intensities of traps for gripped object)
  – Real-time trajectory planning

Focus on manipulation of cells using optically-trapped microspheres (beads) as grippers to minimize damage due to laser exposure
Automation: Need for Perception

Workspace image

Optical tweezers

Laser beam focal positions and velocities

Real-time motion control

Perception (Image processing)

Operation parameters (laser power, manipulated objects, object and fluid medium properties, etc.)

Collision-free trajectories for cells to reach goals

System dynamics modeling

Estimated locations and orientations of cells and microparticles

Operation objectives and constraints

Path planning under uncertainty

Manipulator design

Number and positions of cell grippers
Problem Formulation

• Given input
  – Set of images from different time-lapse experiments
    ▪ Beads and irregular-shaped cells
    ▪ Beads and spherical cells

• Desired output
  – Centroids and diameters of beads; diameters and orientations of cell bounding boxes
Robust Image Processing Method
Examples of Processed Images

- Able to detect object positions and orientations even when they are of different types and located close to each other.
Detecting Irregular-Shaped Cells and Beads

Test image

Our method

Otsu’s thresholding

Histogram equalization & manual thresholding
Detecting Spherical Cells and Beads

Test image

Our method

Otsu’s thresholding

Manual thresholding
Performance Comparison

![Chart showing performance comparison between methods]

- **Our method**: Lower percentage error compared to Otsu's and manual thresholding.
- **Otsu's thresholding**: Moderate percentage error.
- **Manual thresholding**: Higher percentage error compared to the other methods.
Automation: Need for Dynamics Modeling & Control

Workspace image

Optical tweezers

Laser beam focal positions and velocities

Real-time motion control

Perception (Image processing)

Operation parameters (laser power, manipulated objects, object and fluid medium properties, etc.)

Collision-free trajectories for cells to reach goals

System dynamics modeling

Operation objectives and constraints

Path planning under uncertainty

Estimated locations and orientations of cells and microparticles

Manipulator design

Number and positions of cell grippers
State-Space Representation

- States are bead positions; control inputs are optical trap (laser beam focus) positions
- Optical trapping forces on beads are modeled using combination of linear and non-linear spring stiffness with different axial and radial components
- Langevin (thermal) forces and observation disturbances are modeled using zero mean Gaussian distributions
- Viscous drag, buoyancy, and inertial forces are also considered

\[ M \ddot{x} = \left( K_{in}(t) \circ (1 \otimes U(t) - x \ast 1^T) \circ e^{-K_{en}(1 \otimes U(t) - x \ast 1^T)^2} \right) \mathbf{1} - B_{drag} \dot{x}(t) - B_o + F \eta \]

\[ F = \begin{bmatrix} \sqrt{2k_B T\gamma} & 0 & 0 \\ 0 & \sqrt{2k_B T\gamma} & 0 \\ 0 & 0 & \sqrt{2k_B T\gamma} \end{bmatrix} \]

\[ y = Cx + \xi \quad \xi \sim \text{Normal}(0, \Sigma) \]

\[ \mathbf{\gamma} = 6 \pi r \mu \quad \eta_i \sim \text{Normal}(0, \sqrt{\delta t}) \]
Model Predictive Controller (MPC)

- MPC simulates system for certain time horizon to compute control trajectory, i.e., sequence of actions
  - Applies only first action
  - Receives feedback and simulates system once again for receding time horizon based on observed states

- Uses quadratic cost function to optimize each control input

\[ J = \sum_{i}^{t} ((x(i) - x_d)^T (x(i) - x_d)) \]
• Bead motions under influence of one or more optical traps correspond well to theoretical and experimental results
  – Optical trapping forces simulated using high-fidelity geometrical optics toolbox
Microsphere Arrangement Formation

• Successful demonstration for simple arrangements in 2D
  – Further work needed for more complex-shaped arrangements involving larger number of objects in 3D
Ongoing Work: Multi-Cellular Arrangement Formation

- Investigate signaling between parenchymal and non-parenchymal cells as function of geometric shapes and distances.
Participants

• Contributors
  – Ph.D. student
    ▪ Manasa Bollavaram
  – M.S. student
    ▪ Keshav Rajasekaran
  – Undergraduate researchers
    ▪ Ekta Samani
    ▪ John Stewart

• Collaborators
  – Purdue University
    ▪ Dr. Sagar Chowdhury
  – University of Southern California
    ▪ Prof. Satyandra K. Gupta
  – University of Washington
    ▪ Daniel Corbett (Bioengineering)
    ▪ Chelsea Fortin (Bioengineering)
    ▪ Dr. Andrea Leonard (Mechanical Engineering)
    ▪ Prof. Nathan Sniadecki (Mechanical Engineering)
    ▪ Prof. Kelly Stevens (Bioengineering and Pathology)