# Integrating touch to motion planning

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# Summary of last presentation

- **Application of using deep reinforcement learning in robots**
- ***Target-driven Visual Navigation Indoor Scenes using Deep Reinforcement Learning***
  - **Learning based target image**
  - **Generalization to many environments**
  - **Transfer of knowledge from the simulation to the real world**
- ***Applying Asynchronous Deep Classification Networks and Gaming Reinforcement Learning-Based Motion Planners to Mobile Robots***
  - **Use of Abstraction map and asynchronous design to deal with delays of deep classifier and lack of computational resource**



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# Motivation

- Imagine grabbing a cup without sense of touch
- Sense of touch recognised to be important in subject-target interaction
  - Vision data only does not provide useful information for interaction between the object and robot

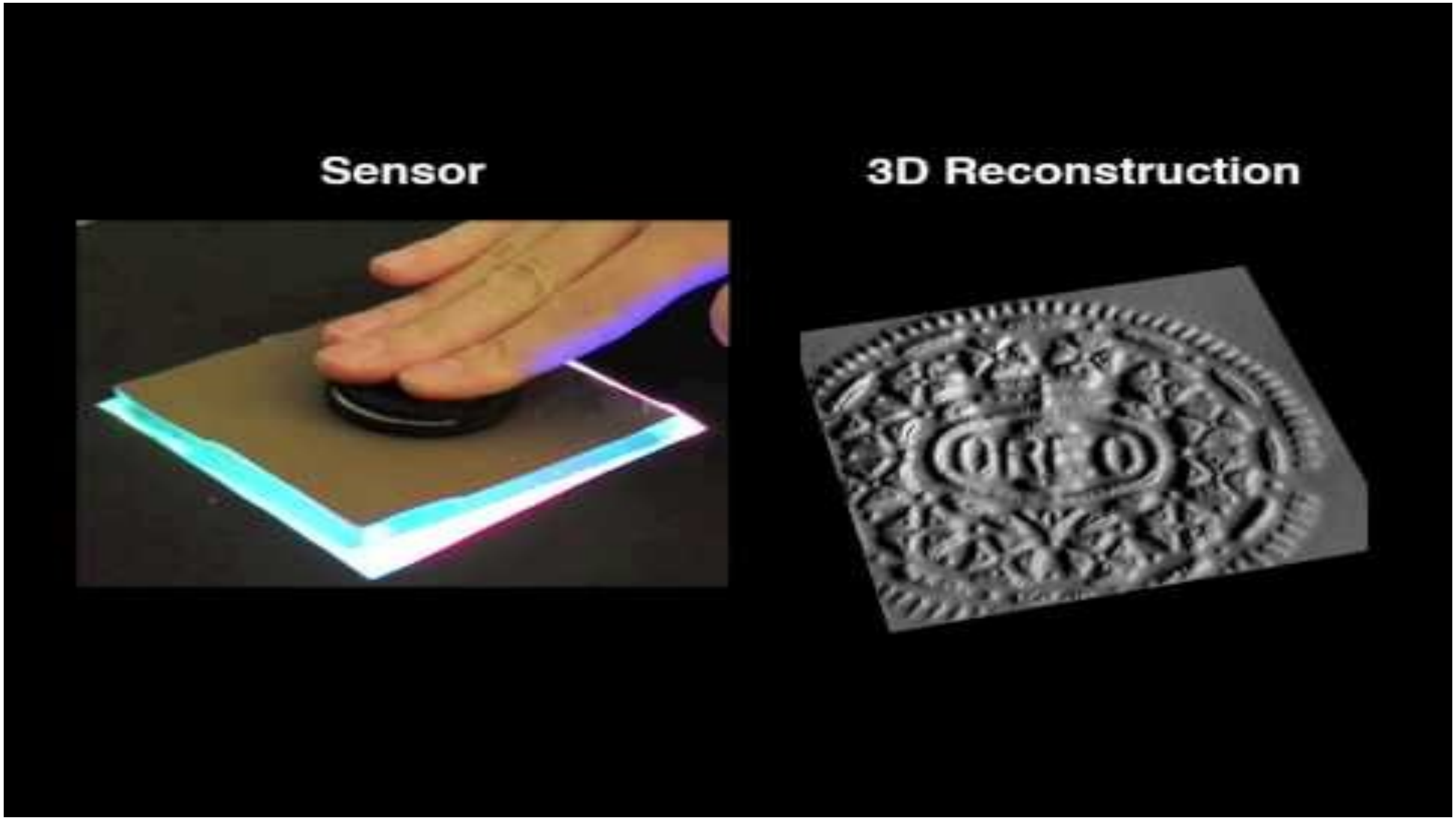
# Previous works

- Touch-based control
  - Estimating stability of current grasp [3]
  - Extracting tactile features to adaptively change the grasping force [4]
- Challenges
  - Limitations of hardware
  - How to integrate tactile sensor to existing control scheme

# Papers

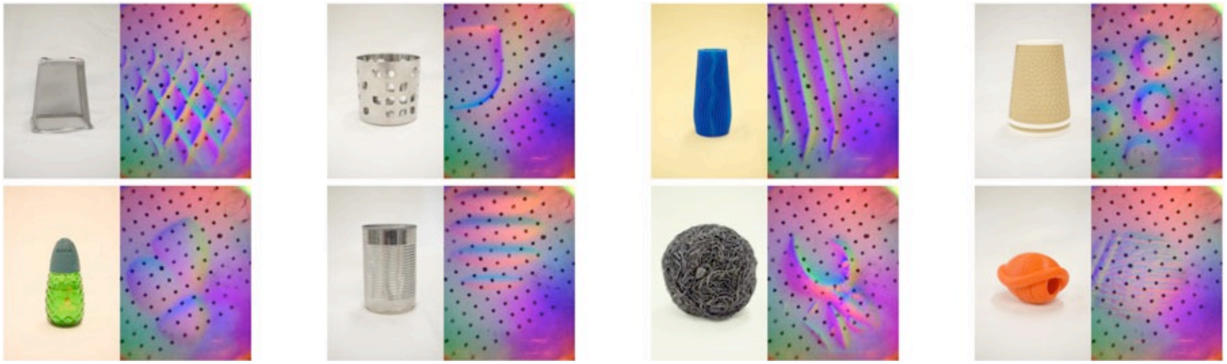
- 1. More Than a Feeling: Learning to Grasp and Regrasp Using Vision and Touch
    - IEEE Robotics and Automation Letters, October 2018
- 2. Manipulation by Feel: Touch-Based Control with Deep Predictive Models
    - ICRA, 2019

# GelSight sensor



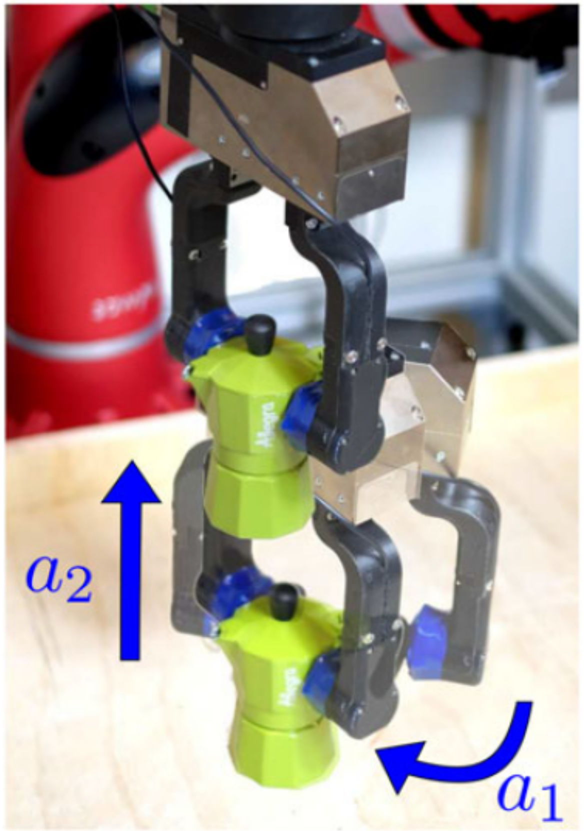
# GelSight sensor

- **Optical tactile sensor with soft elastomer painted with a reflective membrane**
  - **Able to observe high-resolution deformation of the contact surface with a camera**
  - **Can be used to calculate the force applied and slip information**
- **Sensory data provided in regular 2D grid image format**



# Learning to Grasp (Paper 1)

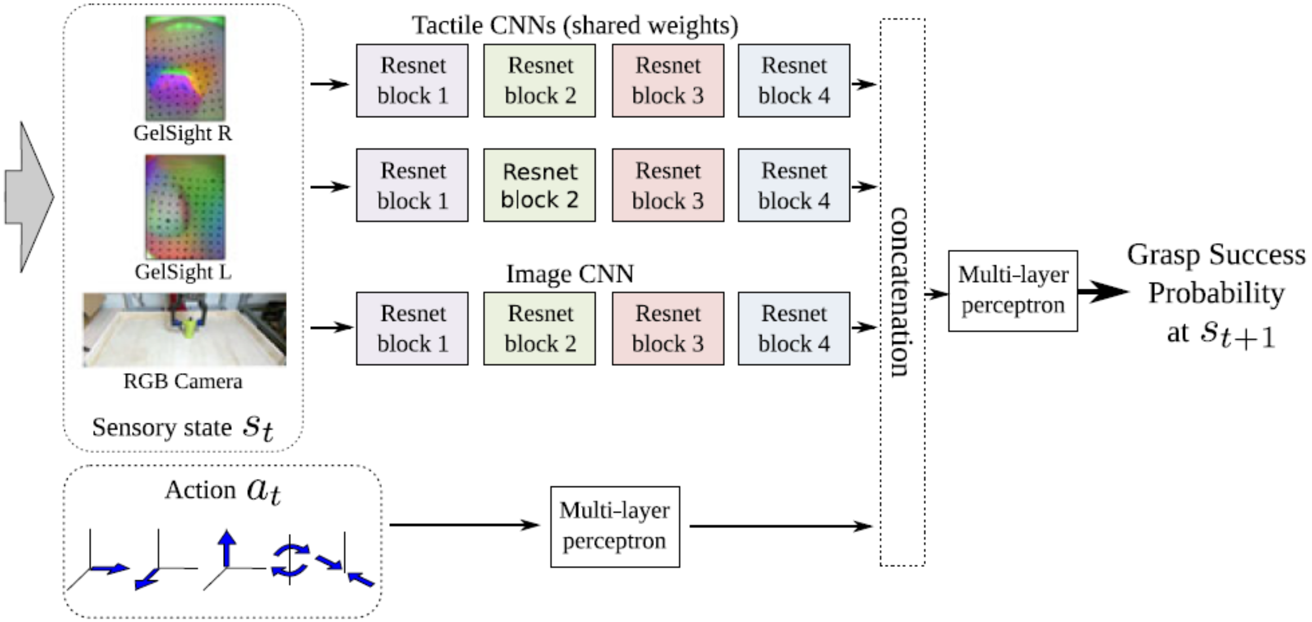
- **Task**
  - **Learning to grasp an object with few regrasps as possible**
- **Robot with RGB camera and two Gelsight sensors, one for each finger.**



# Action-conditional model

- **Prediction problem:**
  - **Variables:**
    - **Current state $s_t \in S$**
    - **Time t**
    - **Action $a \in A$**
      - Translation, rotation, applied force, position of robot
  - **Trying to predict the probability of the robot successfully grabbing the object at time t+1 after applying the action a to $s_t$**

# Overall model



# How robot operates

- **1) Observe current status**
- **2) Randomly sample possible actions**
- **3) Choose the action with the highest probability of successful grab and execute it**
- **4) If the probability exceeds 90%, grab the object**

# Data collection

- **Self-supervised automated data collection**

- **1. Collect grasping trials**
  - **Position of end-effector near to the object**
  - **Random orientation and force**
  - **Labelling of data done by deep neural network trained to detect contacts using the GelSight images (1 – successful, 0 – unsuccessful)**
- **2. Use configurations, define actions as change in configuration**

# Result - Comparison

TABLE I

K-FOLD (K = 3) CROSS-VALIDATION ACCURACY OF THE DIFFERENT MODELS TRAINED WITH 18,070 DATA POINTS

| Model | Accuracy (mean $\pm$ std. err.) |
|---|---|
| Chance | $62.80\% \pm 0.85\%$ |
| Vision (+ action) | $73.03\% \pm 0.24\%$ |
| Tactile (+ action) | $79.34\% \pm 0.66\%$ |
| Tactile + Vision (+ action) | $\mathbf{80.28\%} \pm \mathbf{0.68\%}$ |
| Tactile + Vision (no action) | $76.43\% \pm 0.42\%$ |

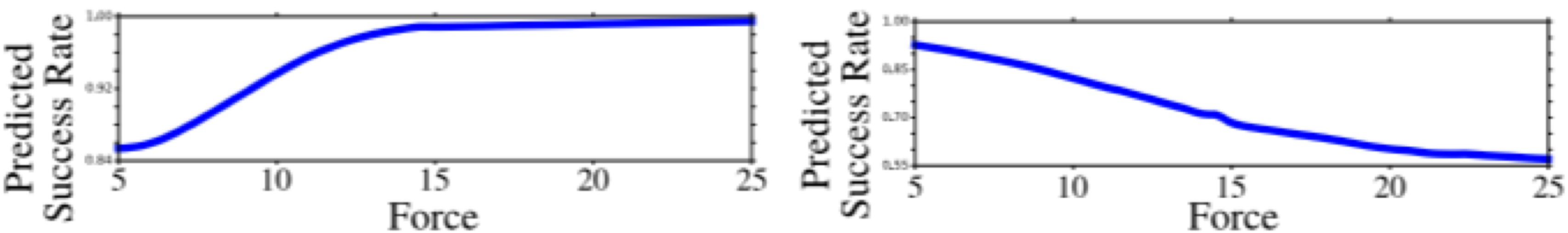
# Result – Grasp evaluation

TABLE II
Detailed Grasping Results Using Different Policies for the "Easy" and "Hard" Test Objects

| "Easy" set | Objects / Methods | 215g | 160g | 40g | 125g | 125g | 65g | 135g | 30g | 380g | 140g | 10g | Average grasp success |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | % grasp success (# success / # trials) | | | | | | | | | | | |
| | Vision only | 76% (38/50) | 70% (7/10) | 60% (6/10) | 50% (5/10) | 50% (5/10) | 90% (9/10) | 40% (4/10) | 60% (6/10) | **90% (9/10)** | 10% (1/10) | **100% (10/10)** | 63.2% |
| | Tactile + Vision | **95% (95/100)** | **100% (10/10)** | **100% (10/10)** | **100% (10/10)** | 90% (9/10) | **100% (10/10)** | **90% (9/10)** | **100% (10/10)** | 80% (8/10) | **90% (9/10)** | 90% (9/10) | **94.0%** |
| | Cylinder fitting | 90% (18/20) | 90% (18/20) | 80% (16/20) | 55% (11/20) | **100% (20/20)** | **100% (20/20)** | **90% (18/20)** | 75% (15/20) | 35% (7/20) | 20% (4/20) | **100% (20/20)** | 75.9% |

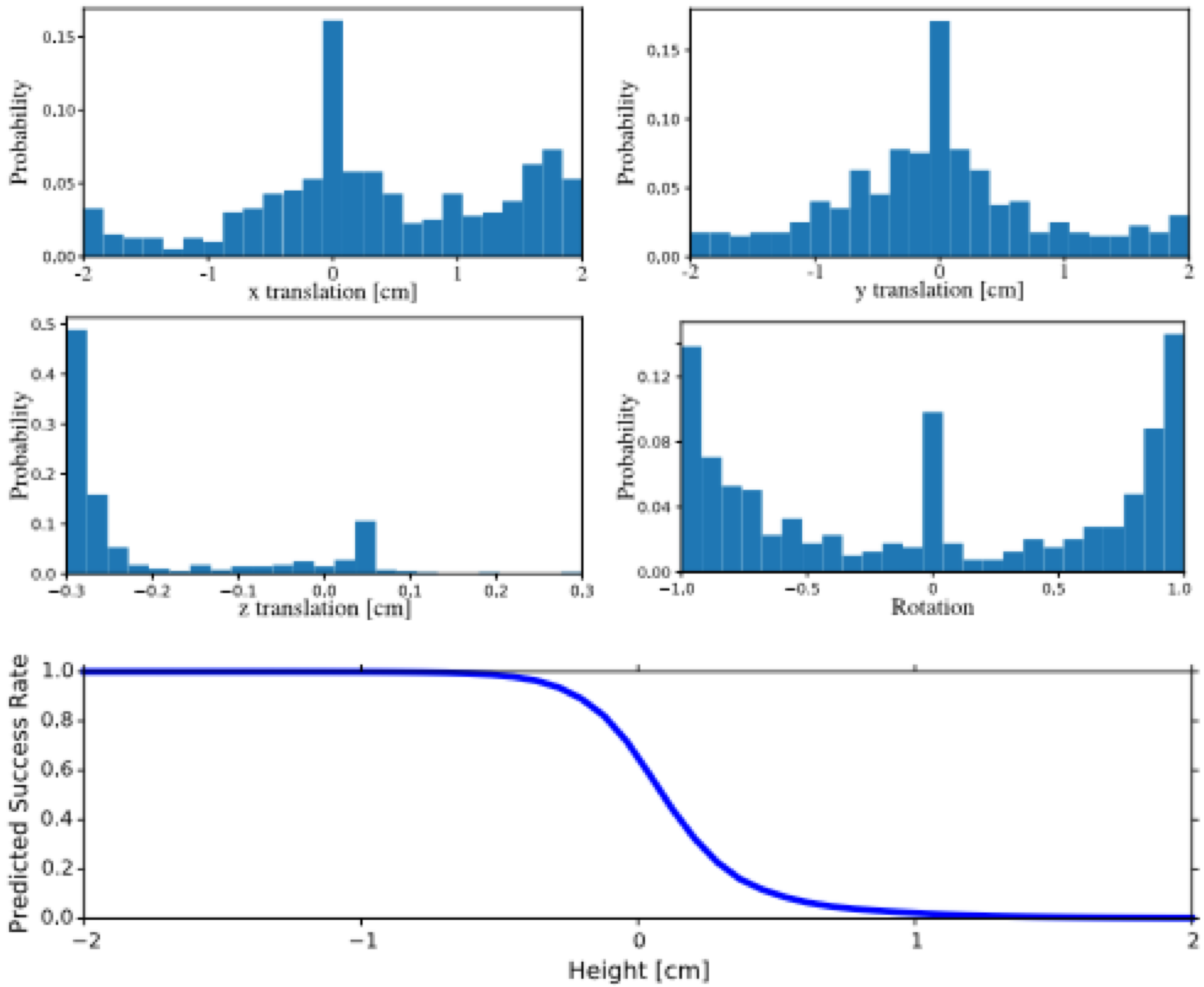
| "Hard" set | Objects / Methods | 230g | 120g | 195g | 50g | 70g | 85g | 38g | 165g | 65g | 340g | 110g | Average grasp success |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | % grasp success (# success / # trials) | | | | | | | | | | | |
| | Vision only | 60% (6/10) | 80% (8/10) | 30% (3/10) | 30% (3/10) | 80% (8/10) | 40% (4/10) | 60% (6/10) | 50% (5/10) | 50% (5/10) | 50% (5/10) | 20% (2/10) | 50% |
| | Tactile + Vision | 80 % (8/10) | **100% (10/10)** | **50% (5/10)** | 80% (8/10) | **90% (9/10)** | **70% (7/10)** | **100% (10/10)** | 40% (4/10) | **60% (6/10)** | **80% (8/10)** | 60% (6/10) | **73.6%** |
| | Cylinder fitting | **95% (19/20)** | **100% (20/20)** | 35% (7/20) | **100% (20/20)** | **90% (18/20)** | 15% (3/20) | 90% (18/20) | **85% (17/20)** | 15% (3/20) | 15% (3/20) | **95% (19/20)** | 66.8% |

# Result – Force vs success rate

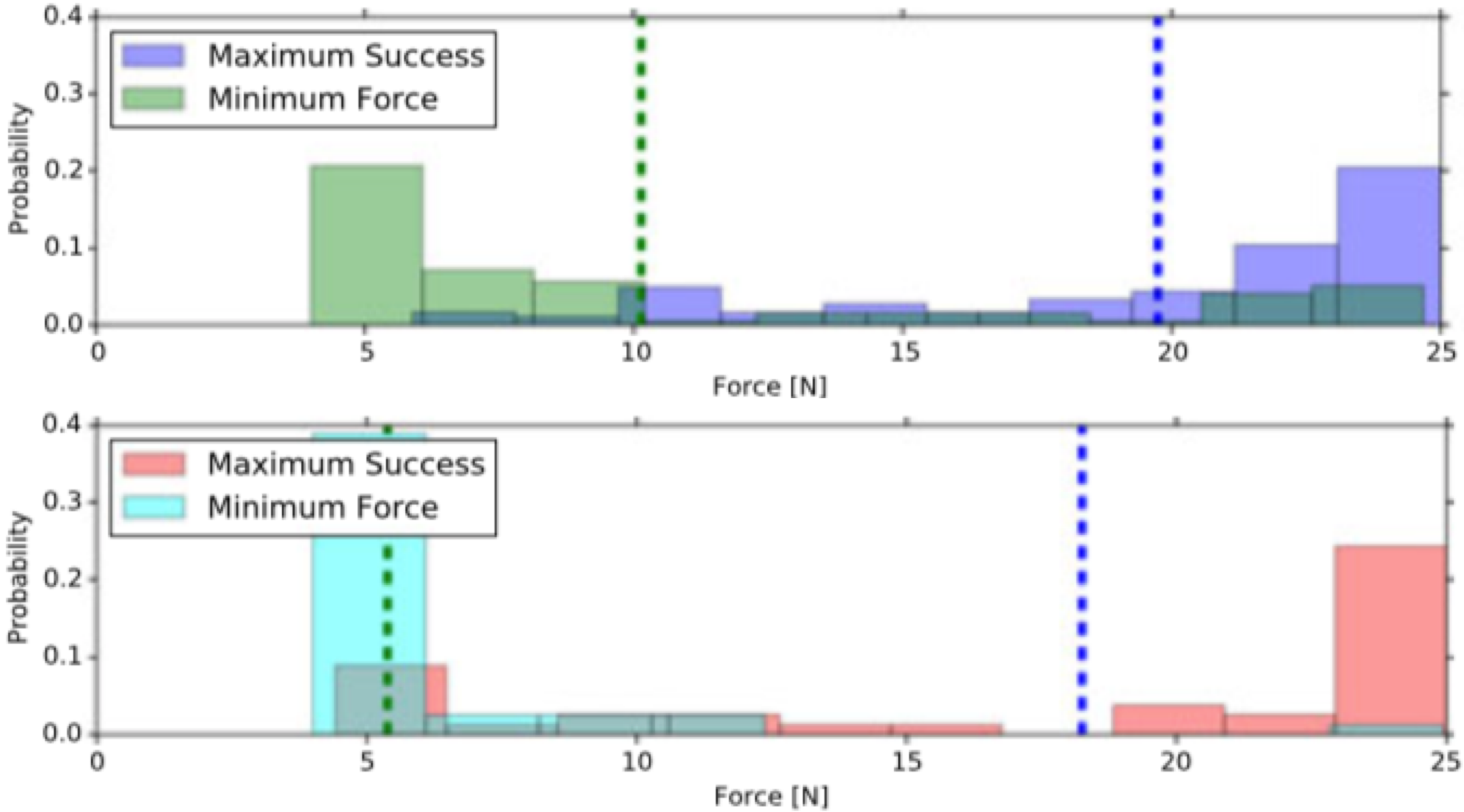



(a) (b)

# Result – Tendency to move down



# Change in policy



# Contribution

- New multi-modal action-conditional model for grasping using vision and touch data
- Effective in grasping novel objects
- Able to introduce additional constraints on contact forces

# Limitation

- Only makes single-step predictions
- Does not perform information gathering actions
- Relatively coarse actions
- Application to real-world environment?

# Manipulation by Feel (Paper 2)

- Tasks
  - 1. Ball repositioning
  - 2. Analog stick deflection
  - 3. Rolling a 20-sided dice
- Robot with one finger, attached with GelSight sensor

# Model-Predictive Control

- **Prediction problem:**
  - **Variables:**
    - **Goal image $I_g$**
    - **Current observation $I_0$**
    - **Time t**

  - **Try to predict best sequence of candidate actions $a_{1:T}$ that after $I_T$, observation after executing those actions similar to $I_g$.**
    - **T (horizon time): time when the sequence of action ends**

# Deep Recurrent Visual Dynamics Model

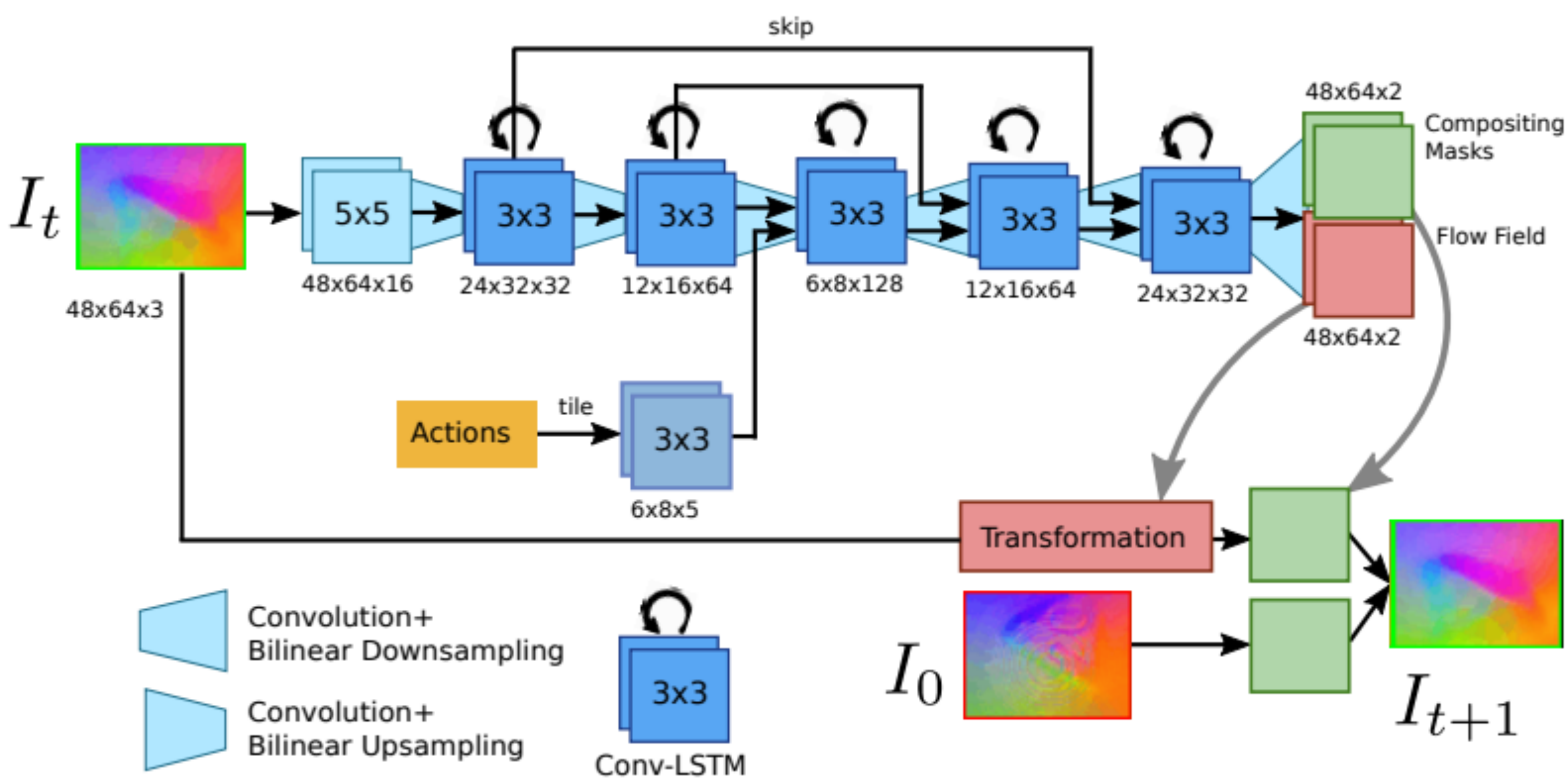
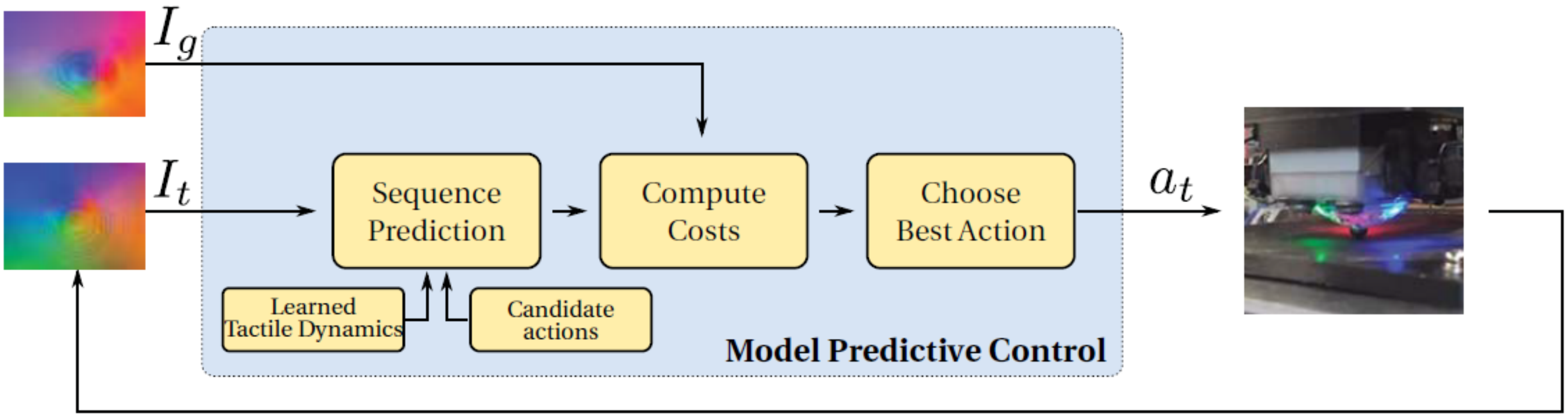



Fig. 11: Video Prediction Architecture.

# Overall model



# How robot operates

- **1) Observe current status**
- **2) Sample sequences of possible actions $a_{1:T}$**
- **3) Find the optimal action sequence**
- **4) Execute only the first action of the sequence**

# Data Collection

- **Autonomous data collection**
  - **Trajectories were collected for each of three tasks**
  - **Applying random movements to robot hand along each of the three axis**

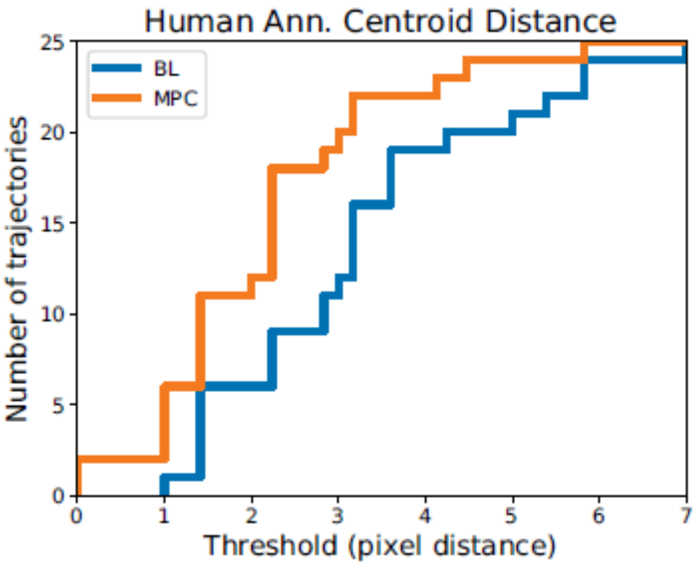
# Evaluation

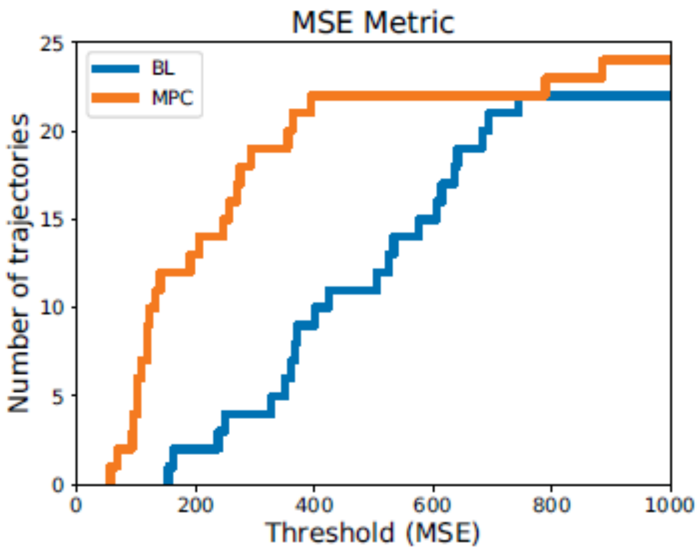
- **Metric**
  - **1) Mean squared error of the difference between the goal-image and observation when the movement is done**
  - **2) Manually annotated distance in pixel-space between the pressure centroid of the object at the end of the trajectory and the location of the pressure centroid in the goal image**
  - **3) (For dice-rolling) the fraction of trials in which the dice could be rolled so that it has the desired face on top**

# Evaluation

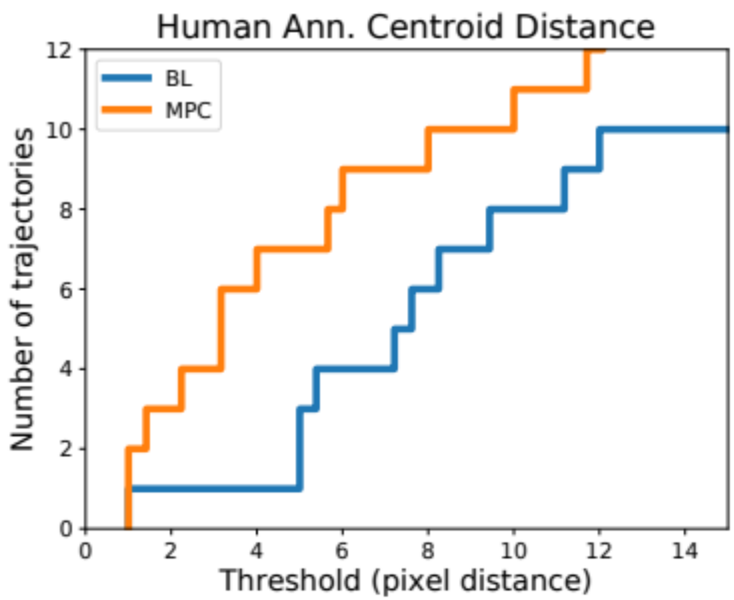
- **Baseline**
  - **Calculates the pressure centre on the imprint of the object the robot is currently touching on**
  - **Calculates the pressure centre on the goal image**
  - **Moves the robot in a straight line from the current pressure centre to goal pressure centre**

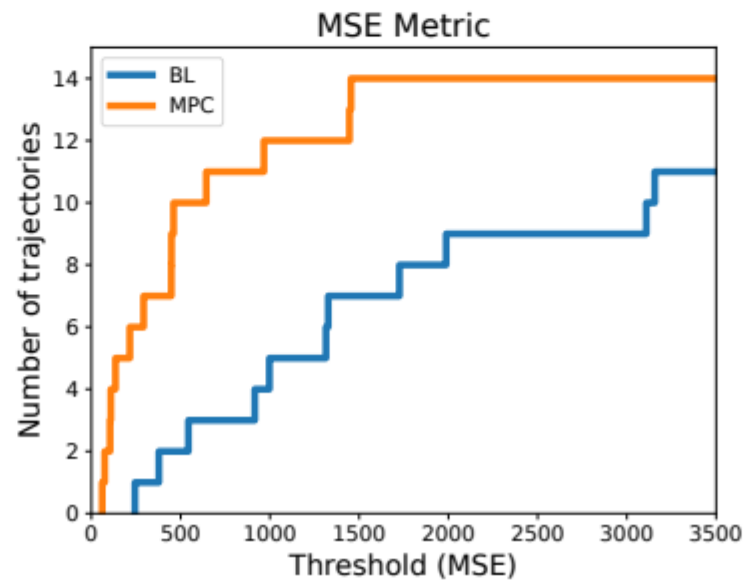
# Result – Ball


Human Ann. Centroid Distance
BL
MPC
Number of trajectories
Threshold (pixel distance)
0
5
10
15
20
25
0
1
2
3
4
5
6
7

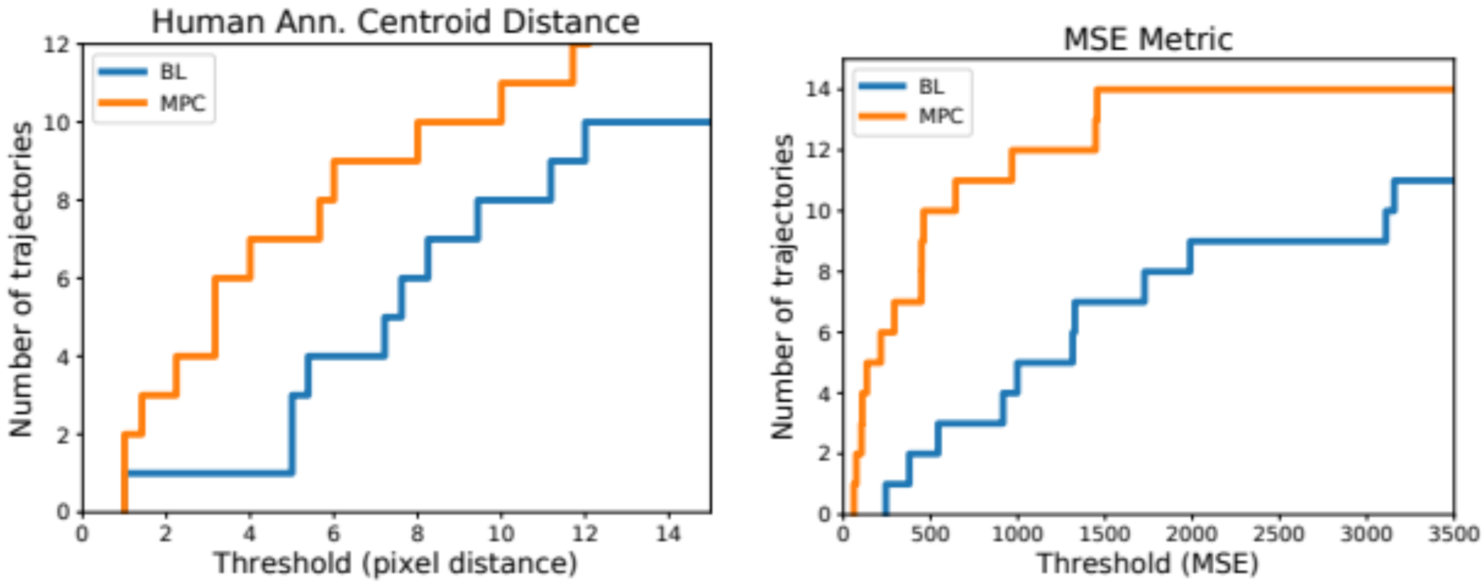

MSE Metric
BL
MPC
Number of trajectories
Threshold (MSE)
0
5
10
15
20
25
0
200
400
600
800
1000

# Result - Dice


Human Ann. Centroid Distance
BL
MPC
Number of trajectories
Threshold (pixel distance)
0
2
4
6
8
10
12
14


MSE Metric
BL
MPC
Number of trajectories
Threshold (MSE)
0
500
1000
1500
2000
2500
3000
3500

# Result - Joystick



# Result – Overall

| | Median L2 dist [mm] | | Success Rate |
|---|---|---|---|
| | Ball Rolling | Analog Stick | Die |
| Tactile MPC | **2.10** | **5.31** | **86.6% (26/30)** |
| Centroid Baseline | 2.97 | 8.86 | 46.6% (14/30) |

# Contribution

- **Training deep model-based control polices directly on high-dimensional tactile sensor data**

- **Training such policy without any rewards**

- **Specifying the goals of policy as data directly from tactile observation space**

# Limitation

- Short horizon time
- Robot arm with single finger
  - Limited range of possible actions

# Overview

| | Paper 1 | Paper 2 |
|---|---|---|
| Tasks | Grasping the objects | 1. Rolling a ball<br>2. Moving a joystick<br>3. Rolling a 20-sided dice |
| Data type used | Vision + tactile | Tactile only |
| Model | Finding the best action that maximizes the grab probability iteratively | Finding the best sequence of actions that minimizes the difference between goal image and observation at the horizon time iteratively. |
| Input | Tactile sensor data, vision data from RGB camera | Tactile sensor data |

# Reference


- [1] Calandra, Roberto, et al. "More than a feeling: Learning to grasp and regrasp using vision and touch." *IEEE Robotics and Automation Letters* 3.4 (2018): 3300-3307.
- [2] Tian, Stephen, et al. "Manipulation by feel: Touch-Based Control with Deep Predictive Models." *2019 International Conference of Robotics and Automation (ICRA), Montreal, QC, Canada, 2019, pp. 818-824.*
- [3] Y. Bekiroglu, J. Laaksonen, J. A. Jorgensen, V. Kyrki, and D. Kragic, “Assessing grasp stability based on learning and haptic data,” *IEEE Trans. Robot.*, vol. 27, no. 3, pp. 616–629, Jun. 2011.
- [4] A. Bicchi, M. Bergamasco, P. Dario, and A. Fiorillo, “Integrated tactile sensing for gripper fingers,” in *Proc. Int. Conf. Robot Vis. Sensory Control*, 1988, pp. 339–349.