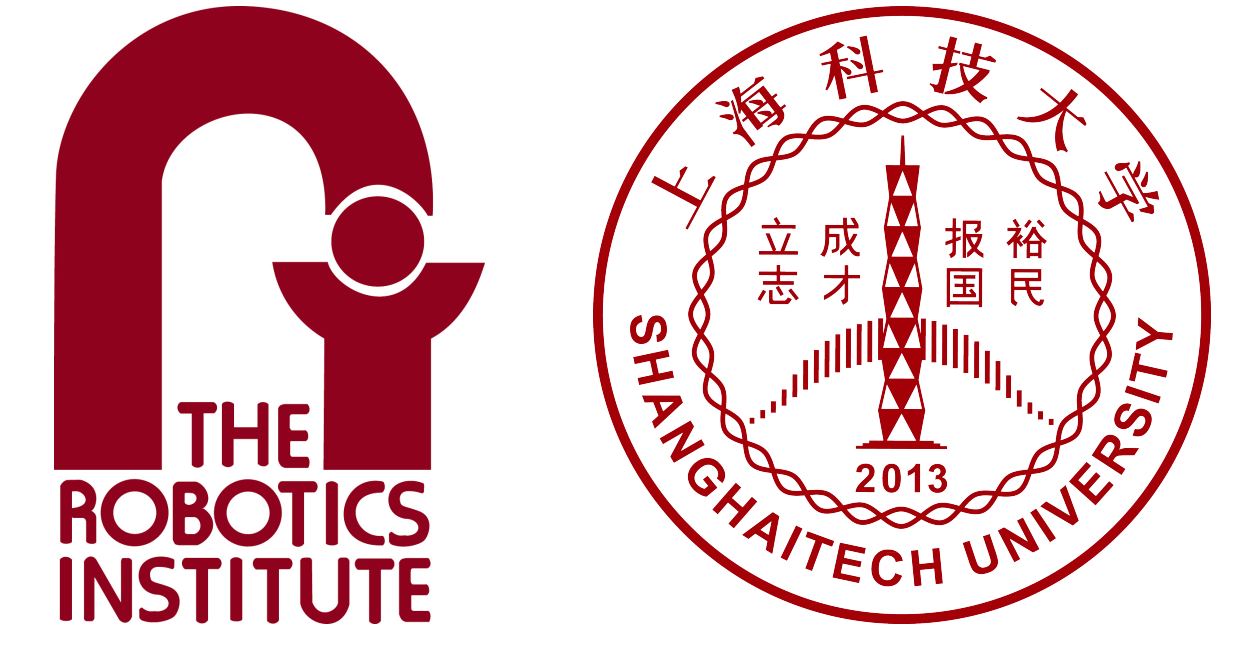


# Tactile only Active Sensing using Reinforcement Learning

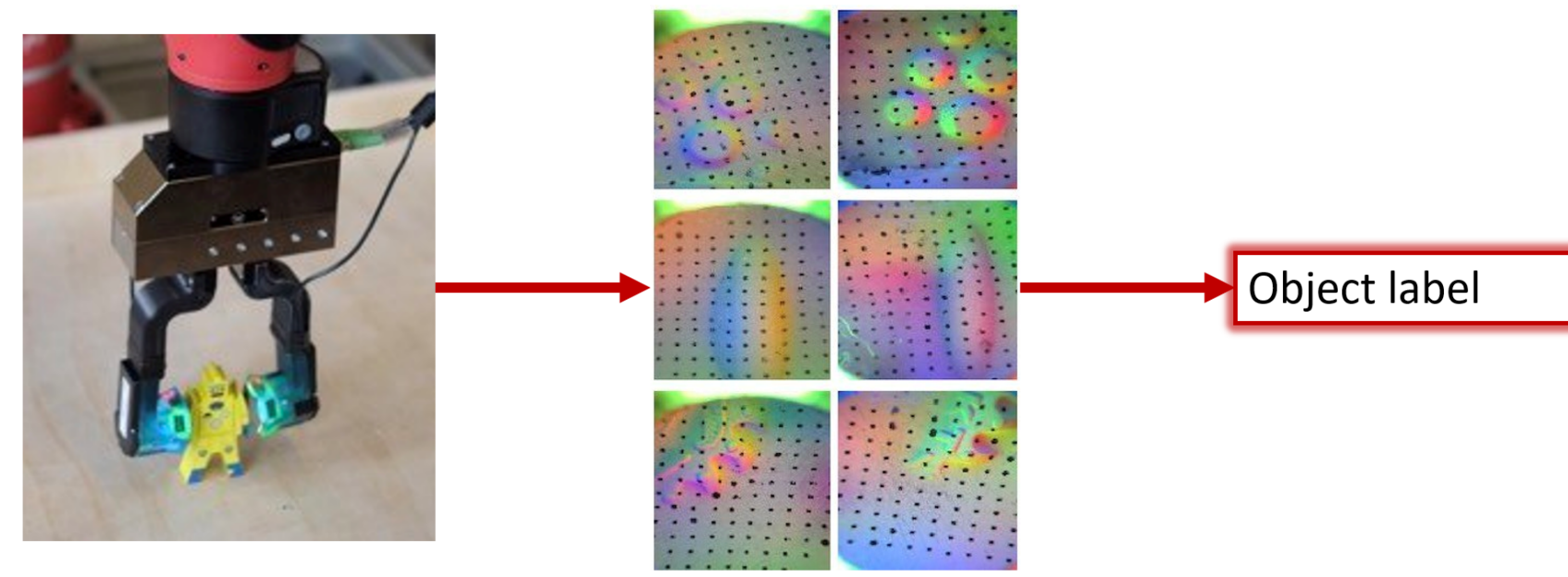
Ziwen Zhuang<sup>1</sup>, Jianren Wang, David Held,

<sup>1</sup>Undergraduate of ShanghaiTech University at RISS Carnegie Mellon University  
zhuangzw@shanghaitech.edu.cn

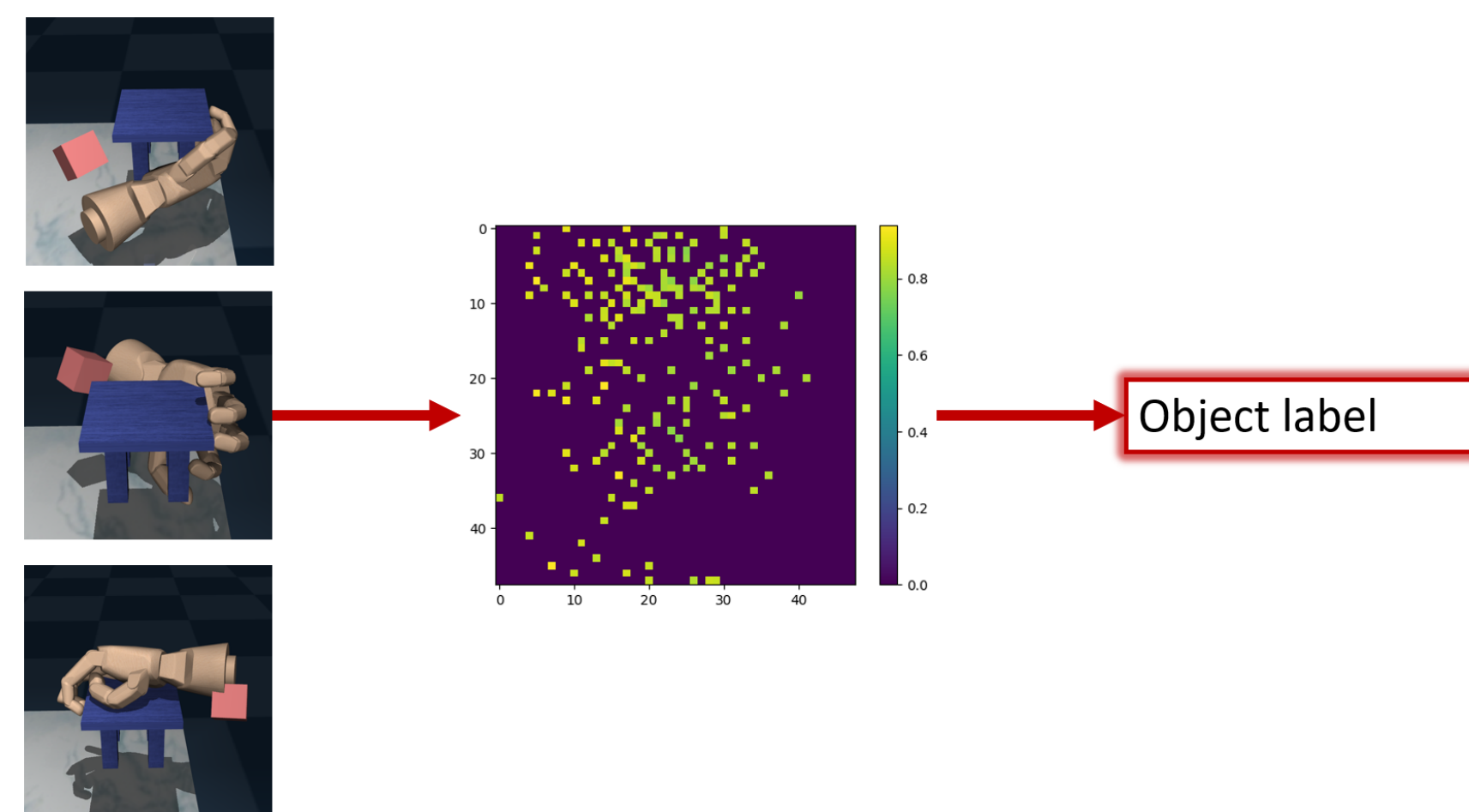


## 1 Introduction

Current works on tactile sensing and recognizing objects using a dense tactile sensor with fixed touching policy. Here we are proposing an active touching policy that improves the tactile information efficiency. And we also proposed an alternative training method to keep improving the cooperation between active touching policy and classification network.



Previous touching policy and classify procedure

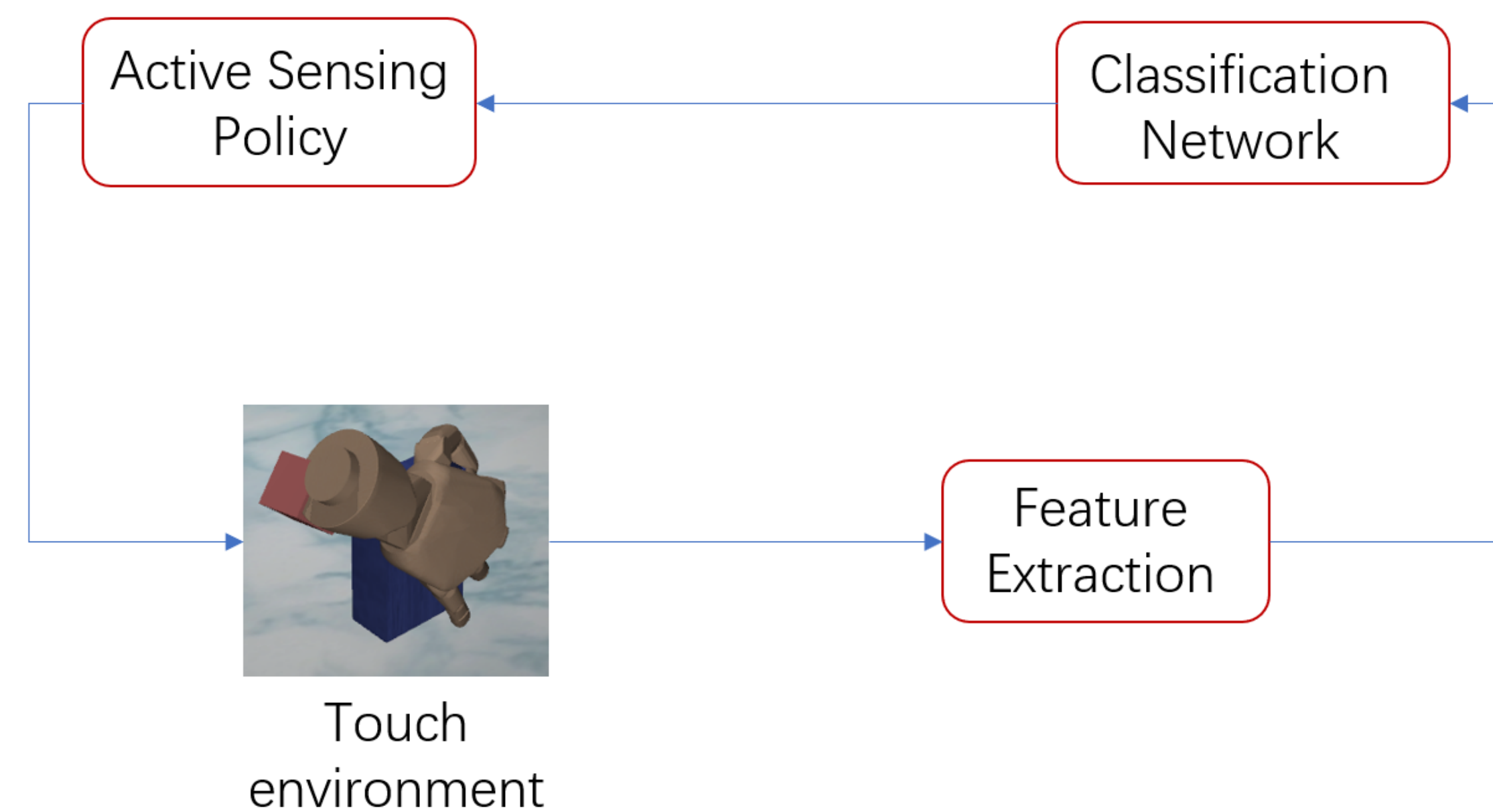


Proposed touching policy and classify procedure

## 2 Methodology

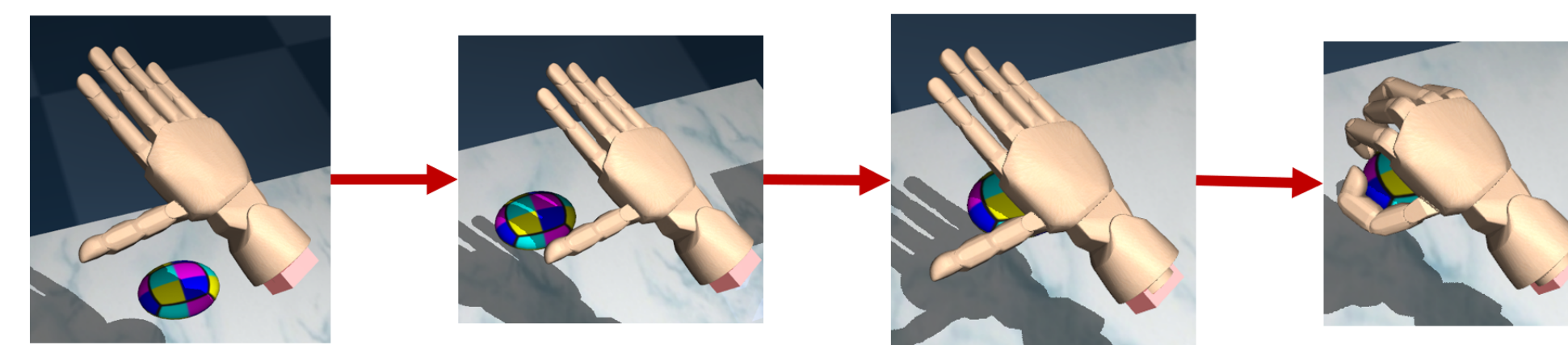
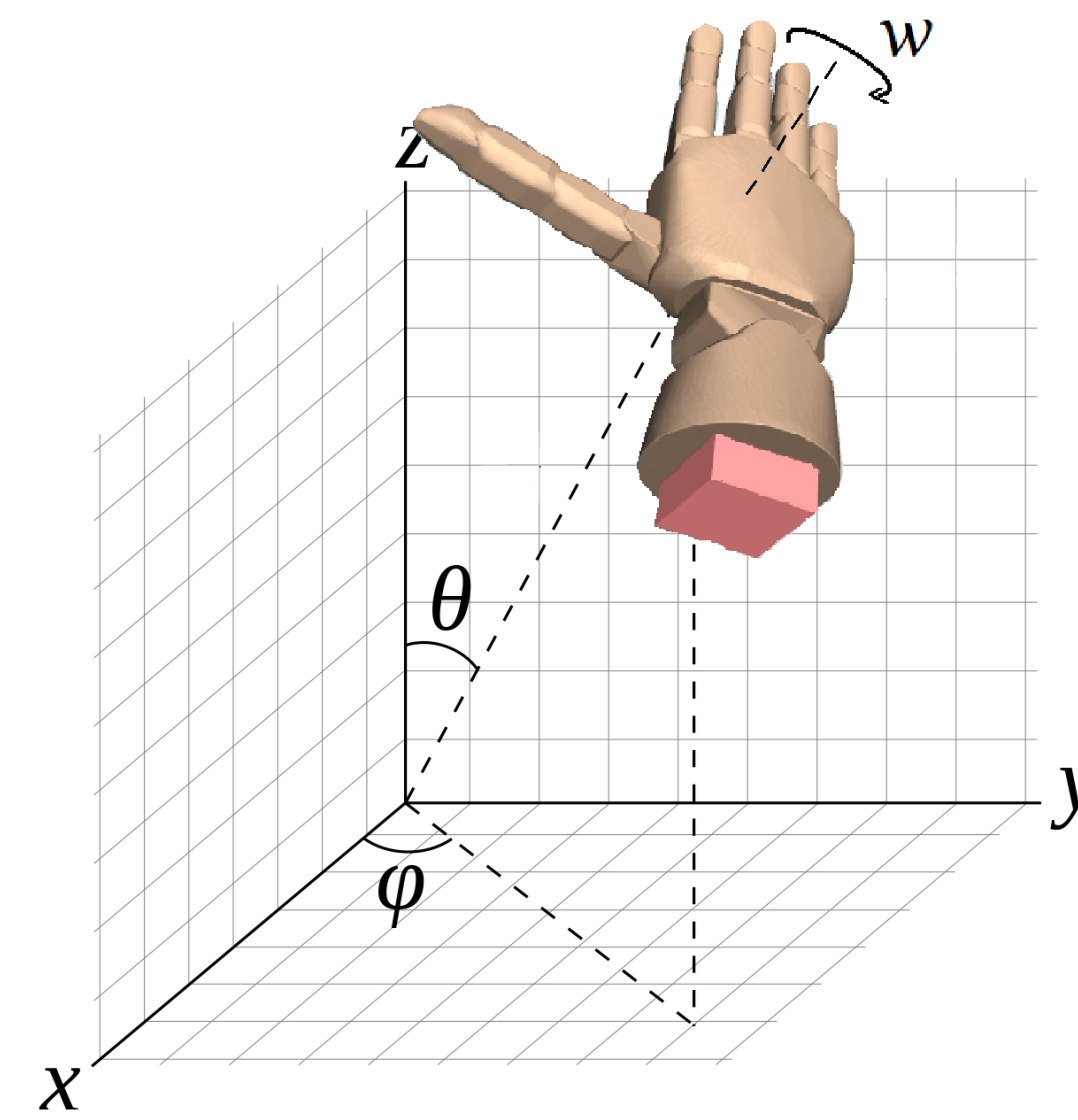
### Active Sensing

Active touching makes a circle where active sensing policy keeps interacting with the touching environment.



### High to Low Level Touch control

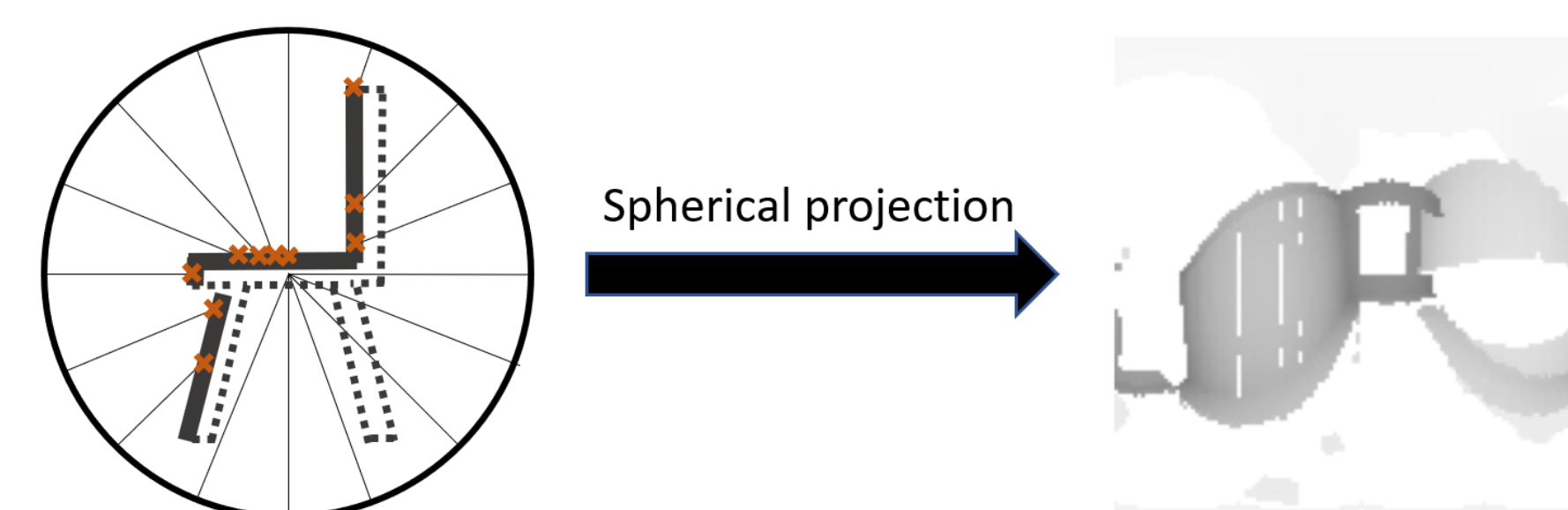
Under high level, the command is represented as a 3D vector, telling controller the spherical direction of getting close and the hand twisting angle.



low level touching sequence

Then, it is able to simplify the learning algorithm action complexity.

### Spherical Projection



Using spherical project to make geometrical feature map

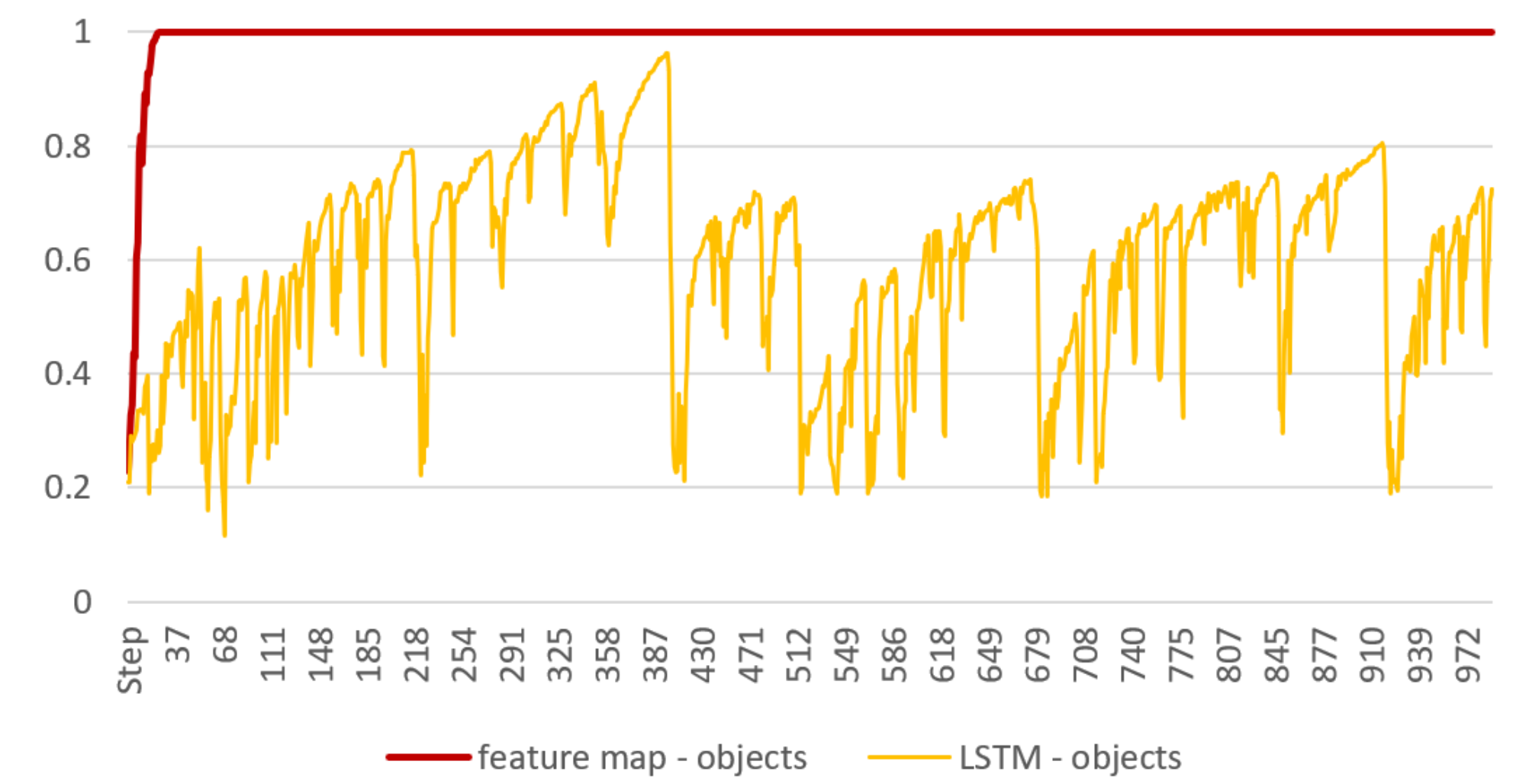
The feature extracted using spherical project is fed in to the classification net and get the classification answer.

### Alternative Training Algorithm

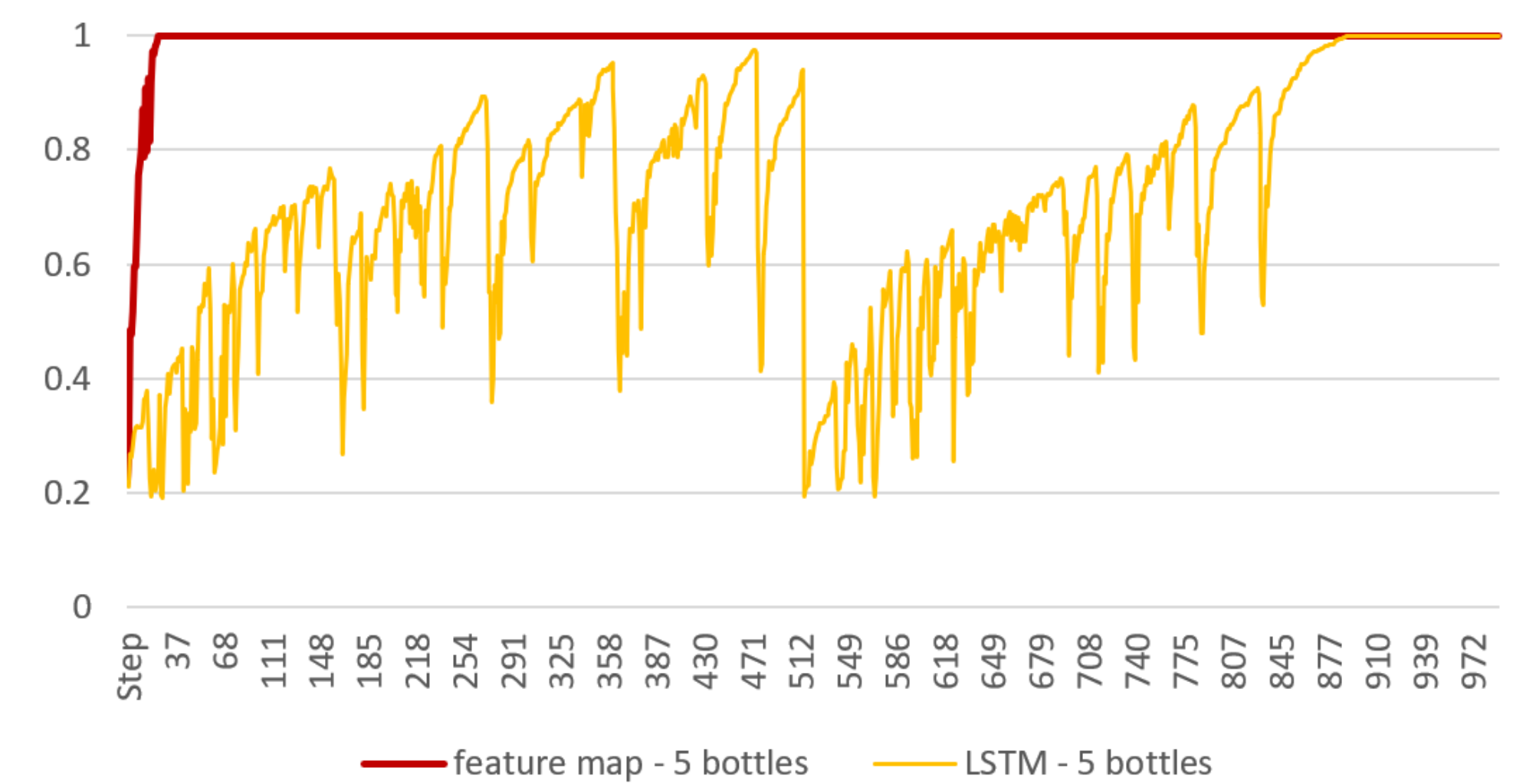
**Algorithm 1** Alternative training classification network and active touching policy

- 1: **procedure** ALTERNATIVELY TRAINING
- 2:   Collect feature image from random touching policy
- 3:   Train classification network using feature map
- 4:   **for**  $i = 1, \dots$  **do**
- 5:     Collect feature image using active touching policy
- 6:     Optimize active touching policy using PPO
- 7:     **if**  $i \bmod t == 1$  **then**
- 8:       Train classify net using latest feature image

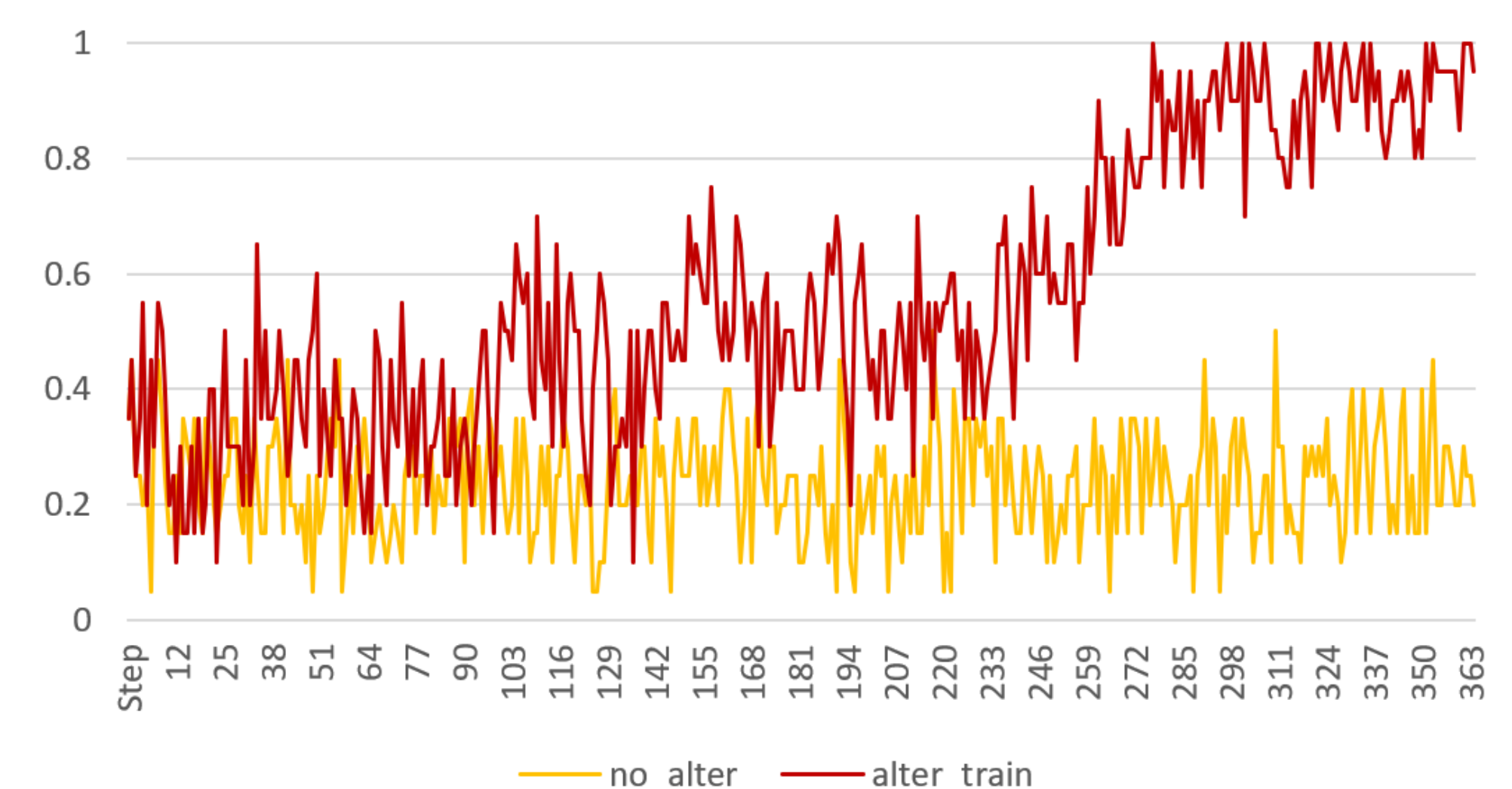
## 3 Result



Accuracy learning curve in 5 primitive objects



Accuracy learning curve in 5 similar shaped bottles



Alternatively training did help improve the classification accuracy, but only training active touching policy only makes the prediction worse.

## 4 Acknowledgement

I would like to thank Dr. David Held for the guidance and support for this project. I'd like to thank Teachers at ShanghaiTech University who facilitate the process of helping me joining the RISS program. And special thanks are given to Rachel Burcin and Dr. John Dolan for their effort in organizing this excellent program.