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# Reinforcement learning for non-prehensile manipulation based on kinaesthetic and tactile feedback

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## Abstract

1      Advancement of haptic sensing technology, such as tactile sensors and sensitive  
2      torque control of actuators, provides richer information about contact force when  
3      manipulating objects with robotic arms. One application of robotic manipulation  
4      that can take advantage of those advanced haptic technology is non-prehensile  
5      manipulation. In this project, reinforcement learning algorithms will be utilized  
6      to learn control policies for haptic-based non-prehensile manipulation of arbitrary  
7      objects on MuJoCo simulator. The task space for the non-prehensile manipulation  
8      is restricted to the two dimensional surface. Various types of paths will be given  
9      as reference paths to follow when manipulating the object using pushing action.  
10     Finally, control policies learned from simulation will be applied to the physical  
11     system if time allows.

## 12    1    Introduction

### 13    1.1   Background

14    People use a lot of strategies to manipulate object. One common example is grasping objects and  
15    move around. However, most of the manipulation is non-prehensile manipulation, which means  
16    manipulation not involving grasping. Non-prehensile manipulation includes actions such as pushing,  
17    pulling, flipping, throwing, and so on. Non-prehensile manipulation is challenging in robotics because  
18    of many reasons. To mention a few of them, non-prehensile manipulation couples grasp planning  
19    and kinematic motion planning and increases uncertainty of feedback from sensors. For example,  
20    occlusion occurs due to the robot hand when the robot uses visual feedback from the camera on the  
21    its head. Because the robot is not grasping the object, the uncertainty increases more than when the  
22    robot is grasping the object. Therefore, haptic feedback is required to have more stable feedback than  
23    visual feedback.

24    Haptic feedback is the combination of kinaesthetic feedback and tactile feedback. For robotic  
25    manipulators, kinaesthetic feedback is obtained by forward dynamics based on the torques of each  
26    joints or force/torque sensor on the end-effector. Tactile feedback is acquired by sensors which are  
27    able to sense normal force, shear force, and vibration. For humans, the sense of touch is a key factor  
28    that enables manual dexterity for humans. Accordingly, there have been a lot of attempts to develop  
29    robust and multi-modal tactile sensors for robots and reliable results came out recently. For example,  
30    GelSight and FingerVision are camera-based tactile sensors and they give not only force and vibration  
31    data, but also proximity visual data. In addition to the tactile sensor, sensitive torque control became  
32    available for actuators. For instance, HEBI Robotics developed a series-elastic actuator with 0.01Nm  
33    torque resolution.

## 34 1.2 Statement of the Problem

35 Can robot manipulate a physically unknown object based on haptic feedback, such as kinaesthetic  
36 feedback and tactile feedback, on two dimensional surface so that the object follows a given path  
37 using non-prehensile actions, such as pushing? To deal with the uncertainty of the friction and inertia  
38 of the object, what kind of reinforcement learning algorithm should be used?

## 39 1.3 Objectives

40 The objectives of this research is to implement an algorithm for learning control policies of haptic-  
41 based non-prehensile manipulation of an arbitrary object guided by reinforcement. Also, MuJoCo  
42 physical simulation will be set up for learning control policies with the implemented algorithm.  
43 Finally, control policies learned from simulation will be applied to a physical system.

## 44 2 Expected Outputs

45 Expected outputs include reinforcement learning algorithm to learn control policies of haptic-based  
46 non-prehensile manipulation of an arbitrary object on MuJoCo simulator. Also, there will be  
47 demonstration of the control policies on physical system composed of 5 DOF manipulator with a  
48 tactile sensor or force/torque sensor.

## 49 3 Methodology

50 Several kinds of reinforcement algorithms, such as natural policy gradient, will be explored to  
51 find proper algorithms that fits to manipulation control application. For physical system, 5 DOF  
52 manipulator from HEBI Robotics will be used with a tactile sensor, called FingerVision, to give  
53 tactile feedback. For kinaesthetic feedback, torque values from each actuator can be used to calculate  
54 forward dynamics or a force/torque sensor, such as Nano 25, can be installed on the end-effector.

55 A specific path, such as straight line, will be given that the object should follow. Then, the robot are  
56 will stabilizing the object as it is moving to the given direction based on haptic feedback. During  
57 the training, the deviation from the given path of the object will be considered as a reward to the  
58 reinforcement learning algorithm.