Manipulation and Tactile Sensing

Intelligent Robotics Seminar

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Outline

- Introduction
- Preliminary experiments
- Advanced tactile sensing and manipulation
- References

Introduction

Robotic arm

- Kinematic chain of base, links, joints, end flange & end effector

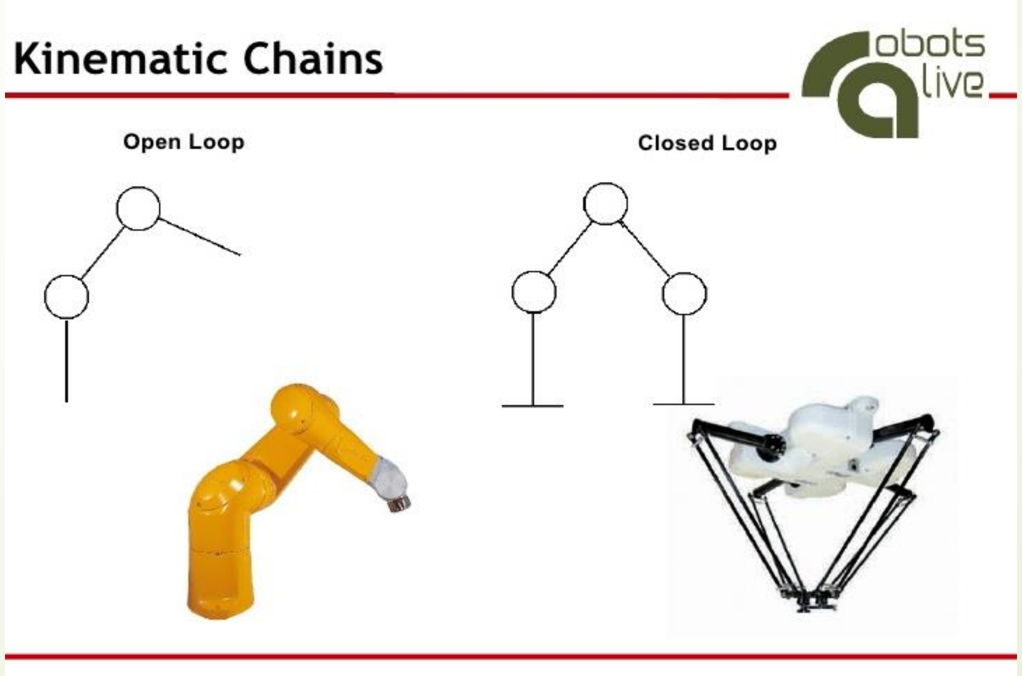


Figure 1 : Robotic arms [3]

Manipulator Kinematics

- Position : pick & place, assembly, stacking
- Velocity : cutting, scanning, painting, machining
- Forward : find position/velocity of end effector
- Inverse : find joint parameter

Tactile Sensors

- physically interact with objects
- detect, measure and convert information to suitable form for use in intelligent systems

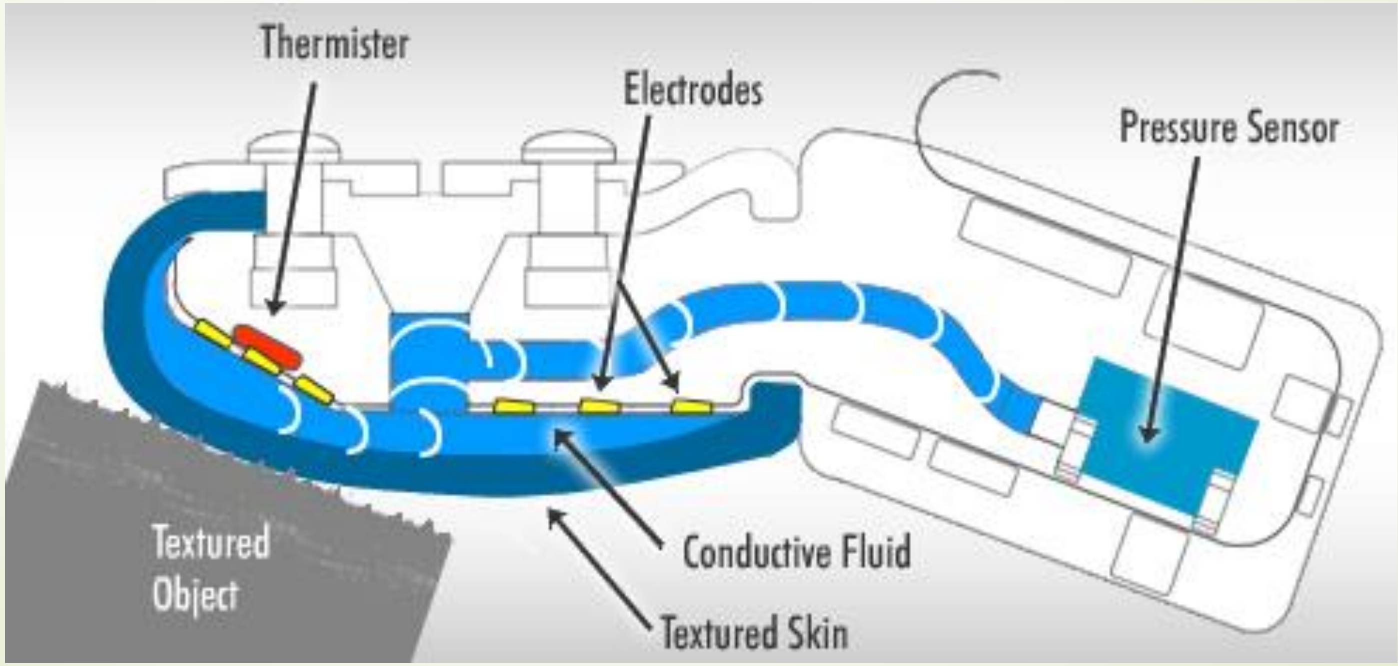


Figure 2 : A tactile sensor [5]

Types of Tactile Sensors

- Normal pressure : Piezoresistive array, Capacitive array
- Skin deformation : Optical, Magnetic
- Dynamic tactile sensing : Piezoelectric (stress rate), Skin acceleration

Preliminary Experiments [1]

- Aim : Flexible and robust robotic manipulation
- Task : Grasp-Lift-Replace an object
- Proposed technology : Dynamic tactile sensors

The Manipulator

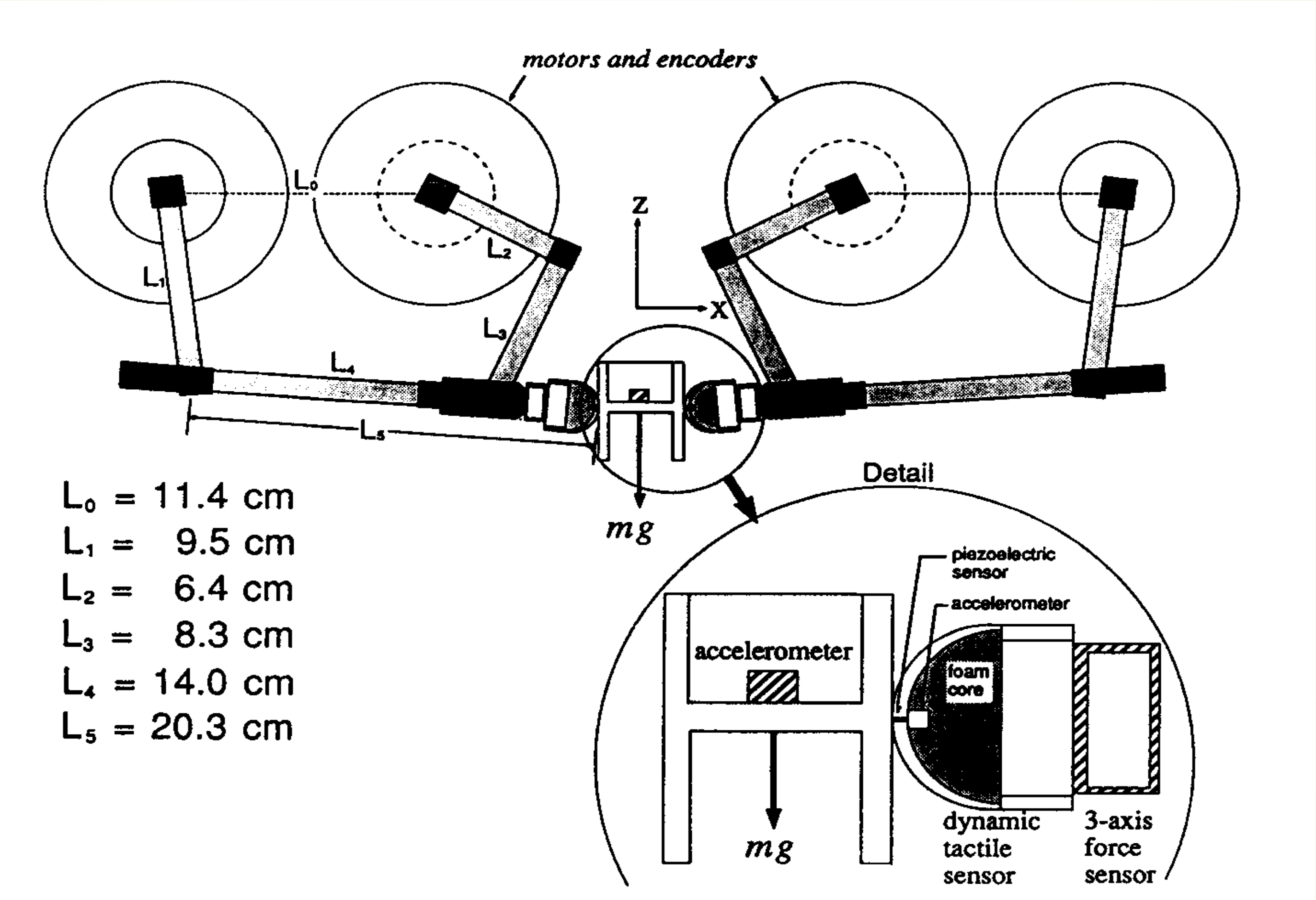


Figure 3 : Experimental setup [1]

Experimental Procedure

- Pre-contact phase
- Loading phase
- Manipulation phase
- Unloading phase
- Post-contact phase

		Phase:	Phase 1 Pre-Contact	Phase 2 Loading	Phase 3 Manipulation	Phase 4 Unloading	Phase 5 Post-Contact
		Transition events:		contact $\dot{x} = 0$ $f_g > 0$	lift-off $\dot{z} > 0$	touchdown $\dot{z} = 0$ $f_t < mg/2$	depart $\dot{x} < 0$ $f_g = 0$
horizontal direction (x)	Desired / bias force $f_{x,d}$		-	$0 \rightarrow f_g$	f_g	$f_g \rightarrow 0$	-
horizontal direction (x)	Desired location X_d		$X_{init} \rightarrow X_o$	X_o	X_o	X_o	$X_o \rightarrow X_{final}$
horizontal direction (x)	Control mode		position	stiffness	stiffness	stiffness	position
vertical direction (z)	Desired / bias force $f_{z,d}$		-	$0 \rightarrow mg/2$	$mg/2$	$mg/2 \rightarrow 0$	-
vertical direction (z)	Desired location Z_d		Z_o	-	$Z_o \rightarrow Z_{max} \rightarrow Z_o$	-	Z_o
vertical direction (z)	Control mode		position	force	stiffness	force	position

Figure 4 : Parameters describing phase transitions [1]

Discussion

Control during phase change

- Requirement : smooth & event-driven transitions
- Solution for smooth transition: sensor on outer skin, foam between accelerometer & force sensor, compliant end effector
- Solution for event-driven transition: dynamic tactile sensor (skin acceleration sensor)

Discussion

Detecting phase change

- One indicator may be faster or more reliable than another in a certain phase
- Dynamic tactile sensor helps in faster indication and deals with uncertainty of object characteristics
- Combination of force sensor signal and tactile sensor signal may be reliable for certain phase change detection

Observation

- Grasp-lift manipulation is easy
- Challenge: smooth & flexible (event-driven) manipulation
- Dynamic tactile sensors must be designed to detect contact status and phase change reliably and without noise
- Force and position sensors are needed for gentle and flexible manipulation.

Advanced Tactile Sensing and Manipulation [2]

- Aim : Object manipulation in an unstructured environment
- Task : Scraping with a spatula in an altered environment

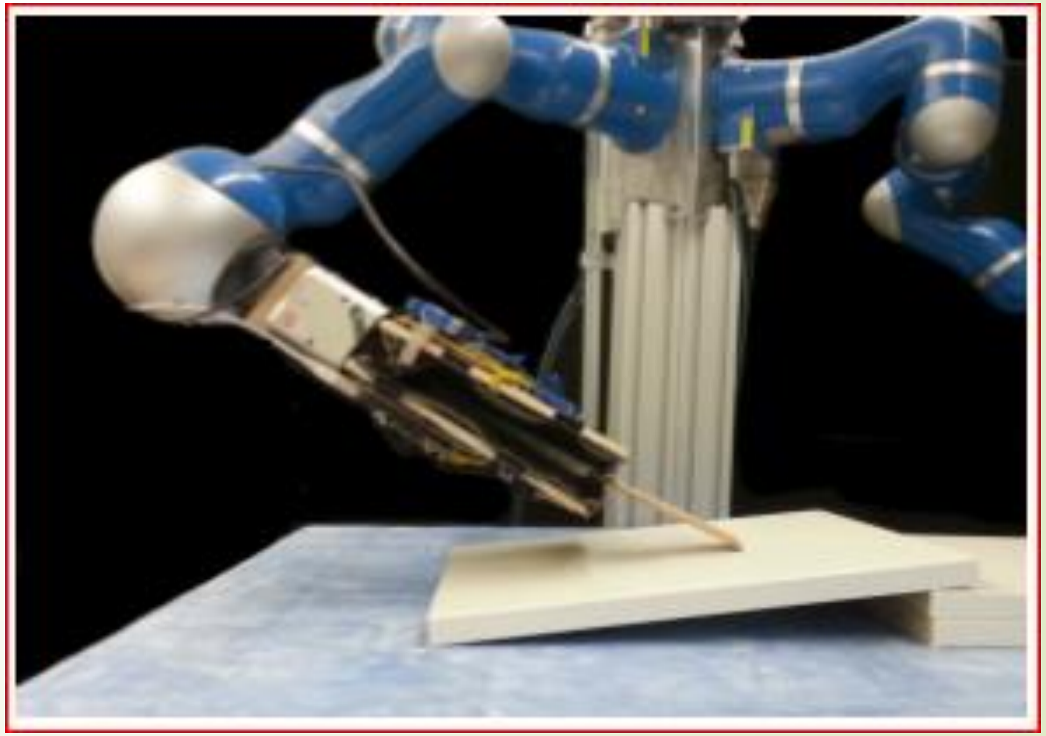


Figure 5 : Robot performing scraping task [2]

Proposed technology : Tactile sensing

- In-hand localization of object
- Dynamic motor primitives
- Perpetual coupling & tactile feedback
- Dimensionality reduction
- Policy search

Localization of object inside the robot hand

- Pose estimation algorithms
  - Learn object model
  - Estimated object pose using learned model
- Here, intensity value vector of tactile image patches are used as features of object appearance

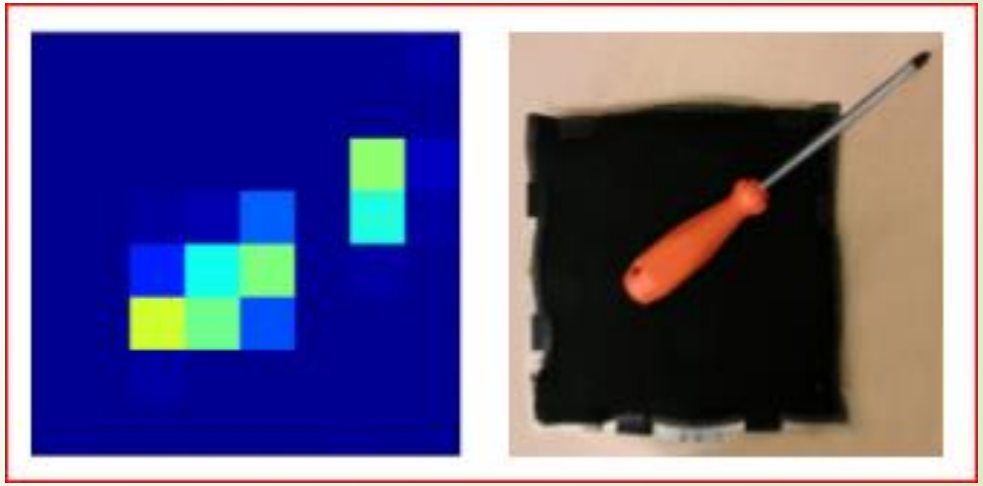


Figure 5 : A tactile image [2]

Dynamic Motor Primitives (DMP)

- Non-linear dynamic system:
  - Spring-damper system
  - Forcing function f(z) driven by canonical system z
- Imitation learning process
- Finds weights such that resultant motion resembles human demonstration

DMP (Forcing function)

$$f(z) = \frac{\sum_{i=1}^{m} \psi_i(z) w_i z}{\sum_{i=1}^{m} \psi_i(z)},$$

$$\psi_i(z) = \exp\left(-h_i(z - c_i)^2\right)$$

Figure 6 : Forcing function formula [2]

m -> number of Gaussian kernels
w -> weight
ψ -> Gaussian

Perpetual coupling & tactile feedback

- Allows change of plan/policy at runtime though tactile feedback
- Tactile feedback = desired tactile trajectory – current tactile signal
- New forcing function = old forcing function + tactile feedback

$$\hat{f}(z) = \frac{\sum_{i=1}^{m} \psi_i(z) w_i z}{\sum_{i=1}^{m} \psi_i(z)} + \sum_{j=1}^{n} \left(\frac{\sum_{i=1}^{k} \hat{\psi}_i(z) \hat{w}_{ij} z}{\sum_{i=1}^{k} \hat{\psi}_i(z)} (\bar{y}_j - y_j) \right)$$

Figure 7 : Updated forcing function after tactile feedback [2]

Dimensionality reduction of tactile information - Motivation

- Number of weights to be learnt is large
- Eg. Consider an 8*8 tactile image.
  - tactile vector length = 64
  - number of Gaussians in model = 50
  - number of weights to be learned for a single DMP = 64 * 50 = 3200

Dimensionality reduction of tactile information - Techniques

- Principal component analysis :

Only parts of tactile image that vary throughout task execution are considered for feedback.

- Weight per phase :

Action is divided into phases by clustering images based on similarity. One weight is learned per phase.

Policy search for learning tactile feedback weights

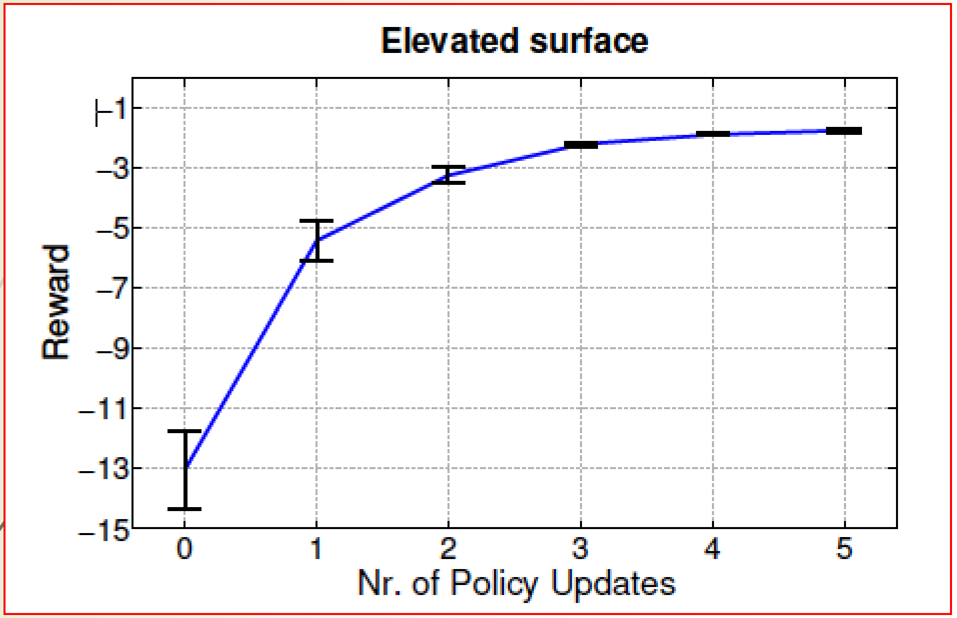
- Optimizes tactile feedback parameter weights (learn controller or robot policy) using reinforcement learning to maximize reward
- Here, Policy optimization is done using episodic Relative Entropy Policy Search (REPS)

Experiment

- Task : Scraping a surface with a spatula
- Test 1 : Elevation of surface by 5cm
- Test 2 : Elevation of surface by 7.5cm (by placing a ramp)
- Goal : Adjust tactile feedback to the dynamically changing height by correcting pressure of spatula on surface

- Working procedure :
  - Learning from human demonstrations
  - For each test, 2 principle components, 3 weights (1 weight per phase of scraping task), 3 DMPs (1 DMP per dimension of 3D Cartesian space) were considered.
  - Number of tactile feedback weights to optimise with REPS = 18.
  - Policy learning process is repeated 3 times per test each consisting of 20 episodes and their resultant policy updates

Experimental Results



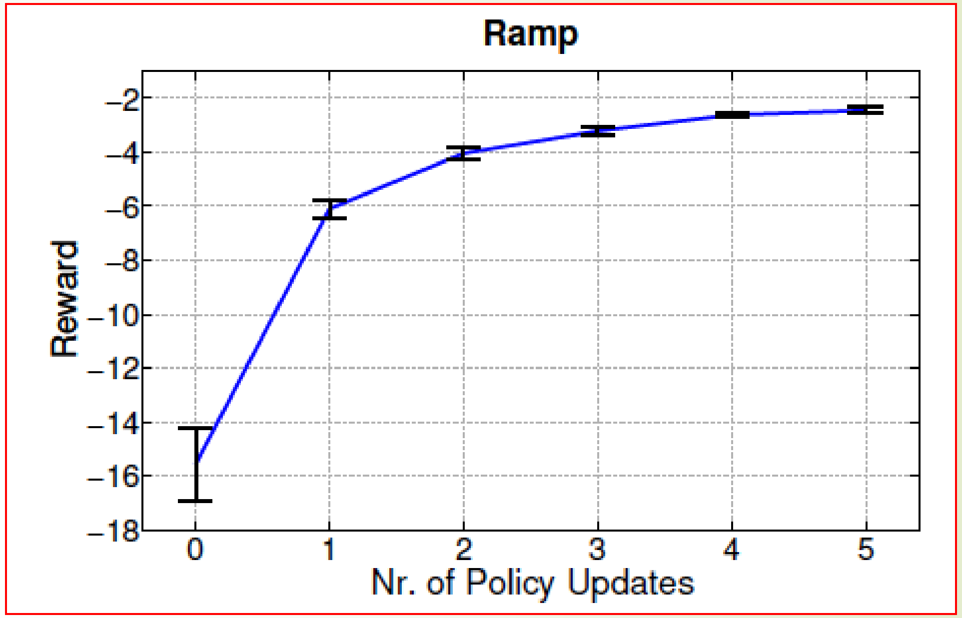


Figure 8 : Mean rewards and standard errors after each policy update [2]

Robot learnt a policy which generalizes to different heights.

Conclusion

- Imitation learning and tactile feedback improves task execution (object manipulation) by robots in an altered environment.

Video 1 : Imitation learning and policy updation [7]

References

[1] Robert D. Howe, Nicolas Popp, Prasad Akella, Imin Kao, and Mark R. Cutkosky, "Grasping, manipulation, and control with tactile sensing," in Robotics and Automation, 1990. Proceedings.,1990 IEEE International Conference.

[2] Yevgen Chebotar, Oliver Kroemer, and Jan Peters, "Learning Robot Tactile Sensing for Object Manipulation," in 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2014).

[3] http://www.slideshare.net/robotsalive/robot-manipulation-basics

[4] Mark R. Cutkosky, Robert D. Howe, and William R. Provancher. Springer Handbook of Robotics : Force and Tactile Sensors.

[5] http://www.medgadget.com/2011/11/techtouch-a-look-under-the-hood-of-an-advanced-tactile-sensor.html

[6] https://studywolf.wordpress.com/2013/11/16/dynamic-movement-primitives-part-1-the-basics/

[7] https://www.youtube.com/watch?v=Ge0GduY1rtE

[8] http://www.scholarpedia.org/article/Tactile_Sensors

Thank You