# Master Thesis Proposal

Compliant Manipulation Using Task Specification and Reinforcement Learning

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# Introduction

# Compliant Manipulation

- Most of the real world robotic manipulation tasks present the need for compliant manipulation.
- Robot needs to respond to the contact forces while executing the task.
- Classical planning and control algorithm fail to perform satisfactorily due to the lack of precise model of contact forces and high computational complexity.

# Problem Statement

# Problem Statement

- We propose to create a framework based on task specification and model based reinforcement learning to solve the problem of compliant manipulation for given task in deterministic manner with fewer number of interactions with environment.
- We will evaluate our approach based by learning the task of opening door and cutting vegetables.

# Related Work

# Task Specification in KRL

Listing 1: KRL code

```
^^I^^IINI
^^I^^IPTP HOME ; go to HOME joint configuration
^^I^^ILIN P1  ; linear motion to point P1
^^I^^ILIN P2^^I ; linear motion to point P2
^^I
```

- Heavily used in industrial settings
- Reliable
- Difficult to integrate sensory feedbacks
- Limited expressive power [5]

# Task Specification in Leidner's PhD work[5]

- Symbolic representation of the task in PDDL.
- Geometric representation of the task specifies the sequence of low level movement sequences needed to complete the action.
- Geometric representation only specifies discrete motion primitives and not the parametric representation of the motion primitives.
- Actual parameterization and control is left to low level control module.

# Task Specification by Meson et. al. [6]

Listing 2: Task Specification using TFF: Open Door

```
^^I^^Imove compliantly {
^^I^^I^^Iwith task frame directions
^^I^^I^^Ixt: force 0 N
^^I^^I^^Iyt: force 0 N
^^I^^I^^Izt: velocity v mm/sec
^^I^^I^^Iaxt: force 0 Nmm
^^I^^I^^Iayt: force 0 Nmm
^^I^^I^^Iazt: force 0 Nmm
^^I^^I} until distance > d mm
^^I
```

- Using hybrid control, various control modes are assigned to each axis of the *task frame* or *compliance frame*[7].
- This framework doesn't consider the specification of task or motion quality related parameters like velocity damping or instantaneous sensory inputs.
- It also specify action to be executed *compliantly* but does not specify the how?

# iTaSC

- iTaSC developed in [1, 2, 3], synthesizes control inputs based on provided task space constraints.
- It formulates a optimization problem considering provided constraints in the environment.
- In case of conflicting constraints, constraints are weighted in the optimization problem.
- Suffers heavily by inaccurate modeling of the constraints.

# Reinforcement Learning for Manipulation

- In model free and model based reinforcement learning, an agent learns the skills by exploring the environment and adopting the parameters which governs the trajectory of the agent in the environment.
- Learning all the parameters of the policy can be computationally very expensive and might require large number of interactions with the environment.
- Large number trials causes wear and tear in mechanical parts and even damage to robot and the environment apart from being time consuming.
- If we can model the environment and constraints on the motion of the robot, we can drastically reduce the number of parameters to be learn to achieve the task.
- Use of reinforcement learning to learn these reduced number of parameters can result in near optimal policy for achieving the task.

# Reinforcement Learning for Manipulation

- Manipulation tasks imply complex contact interactions with an unstructured environment and require a controller that is able to handle force interactions in a meaningful way [4].
- Planning algorithms would require precise dynamics models of the resulting contact interactions.
- These models are usually unavailable, or so im-precise that the generated plans are unusable[4].
- Kalakrishnan et. al. in [4] proposed an intelligent control algorithm with reinforcement learning for opening door task.
- It considers the constraints on door motion greatly reducing, the number of parameters to be learned.

# Proposed Solution

We plan to solve a compliant manipulation task by providing task specification and then tuning the task parameters with the help of re-reinforcement learning.

Examples of task modeling:

Listing 3: Task specification for opening door

```
^^Iopen_door
^^I{
^^I^^If_x = f(environment, robot, task)
^^I^^Iv_y = v1
^^I^^Imax_acc = a_max
^^I^^Imax_dec = a_dec
^^I}until(f(...))

^^I
```

Listing 4: Task specification for cutting vegetables

```
^^Iopen_door
^^I{
^^If_z = f(environment, robot, task, v_x)
^^Iv_x = g(t)
^^Imax_acc = a_max
^^Imax_dec = a_dec
^^I}until(f(...))

^^I
```

- Force specification on compliant axis

# Composition

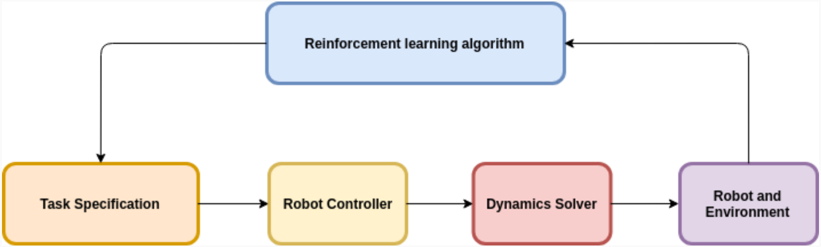


**Figure 1:** Composition

# Reinforcement Learning Algorithm to be Used

- We plan to use Path Integral Policy Improvement algorithm for learning[4].
- $PI^2$ Algorithm is a probabilistic algorithm for policy improvement.
- Multiple works so far has proven the capability of $PI^2$.

The aim is to minimize the expected cost of each cycle which is given by:

$$J(W) = c_t + \int_{t_0}^{t} (c_i(t) + \frac{1}{2} W^T R W) dt$$

$c_t$ is terminal cost. $c_i(t)$ is instantaneous cost at instant $t$. $R$ is the weighting matrix, which minimizes control cost. $W$ is policy parameter matrix.

# Advantages

- Task specification is a practical approach for solving manipulation.
- Scope for representing motions in multiple type of motion primitives. e.g. DMPs
- Reinforcement learning replaces the need of model accuracy.
- This approach will require less number of robot-environment interactions as compared to other reinforcement learning approaches.
- This solution bridges the gap between task specification approaches and learning methods fo compliant manipulation.

# Challenges

- Task specification and parameterization
- Design of reward function
- Safety of the robot

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