Continuous control of a Robot Manipulator using Deep Deterministic Policy Gradient

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Outline

Motivation

Few applications of Robot Manipulator

- **Industrial**: welding, painting, assembly, disassembly, pick and place
- **Medical**: invasive surgeries, prescription dispensing systems

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Reinforcement Learning:-

- Ability to generate optimal policies with no prior knowledge of the environment
- Deep RL addresses the issues of scalability, memory and computational complexity
- Can extend to multiple degrees-of-freedom

Related Work

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- No performance evaluation in the presence of uncertainties and disturbances

Robot Manipulator Dynamics

The dynamics of the robot manipulator is described as follows:

$$M_{11}\ddot{\theta}_1 + M_{12}\ddot{\theta}_2 + V_1 + G_1 = \tau_1 \qquad (1)$$

$$M_{12}\ddot{\theta}_1 + M_{22}\ddot{\theta}_2 + V_2 + G_2 = \tau_2 \qquad (2)$$

In a more standard form:

$$M(\theta)\ddot{\theta} + V(\theta, \dot{\theta}) + G(\theta) = \tau \qquad (3)$$

where,

$$M = \begin{pmatrix} M_{11} & M_{12} \\ M_{12} & M_{22} \end{pmatrix}, V = \begin{pmatrix} V_1 \\ V_2 \end{pmatrix}, G = \begin{pmatrix} G_1 \\ G_2 \end{pmatrix}, \tau = \begin{pmatrix} \tau_1 \\ \tau_2 \end{pmatrix}$$

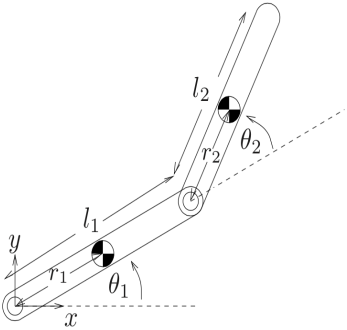

Figure: TLRM

Goal: Track a desired reference, $\theta^* = [\theta_1^*, \theta_2^*]^T$

Reinforcement Learning

- Learning takes place through agent-environment interactions
- At each time-step t, agent takes an action A_t based on the current state S_t, giving rise to a new state S_{t+1} receiving an immediate reward of r_t while following a policy π

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- The goodness of a state is determined by its value function:

$$V_\pi(s) = \mathbb{E}_\pi\left[R_\pi | S_t = s\right] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k r_{t+i+1} | S_t = s\right] \tag{5}$$

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- Similarly, the value of taking an action a in state s while following a policy π is given by:

$$Q_\pi(s,a) = \mathbb{E}_\pi\left[R_\pi | S_t = s, A_t = a\right] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k r_{t+i+1} | S_t = s, A_t = a\right] \tag{6}$$

Introduction to Deep Deterministic Policy Gradient (DDPG)

- Why DDPG?
  1. Proposed as a simple integration of deep Q-networks and actor-critic
  2. Successful in operating over continuous action spaces
  3. As the uncertainties and disturbances are deterministic in nature, a deterministic policy is sufficient to achieve our targets
- There are 4 main steps to this process:
  1. Experience replay; Finite-sized cache D
  2. Actor & critic networks: $\mu(s|\theta^{\mu})$ and $Q(s, a)$
  3. Target network updates: Added stability during training, $\theta_t = \rho\theta + (1-\rho)\theta_t$
  4. Exploration: Adding an appropriate noise signal, $\mathcal{N}$

DDPG-based Controller Specifications

- DDPG-based controller is augmented with a stabilizing PD controller
- $\Delta\tau_1$ and $\Delta\tau_2$ compensate for the uncertainties in the system

$$R = -e^T Qe \qquad (7)$$

where $e = \theta - \theta^*$ and Q is a positive definite matrix.

- Few of the DDPG parameters:

Parameter	Description	Values
(α_a, α_c)	Learning rates	$(0.001, 0.002)$
γ	Discount factor	0.99
$\Delta\tau$	Action Space	[-1,1] Nm

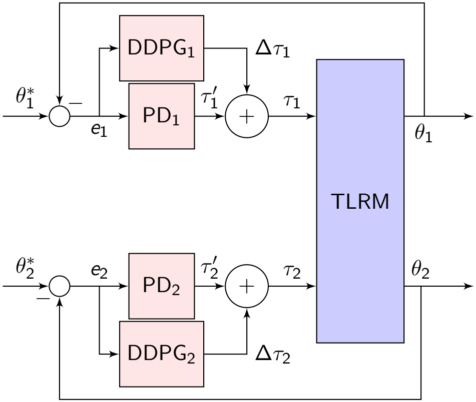


Figure: TLRM controller framework

Description of Uncertainties

- **Frictional Forces**
  1. Friction that is present between the joints of the robot manipulator can severely affect motion quality
  2. The frictional matrix can be modelled as:

$$F(\dot{\theta}) = \begin{bmatrix} \nu_1\dot{\theta}_1 + k_1 \text{sgn}(\dot{\theta}_1) \\ \nu_2\dot{\theta}_2 + k_2 \text{sgn}(\dot{\theta}_2) \end{bmatrix} \tag{8}$$

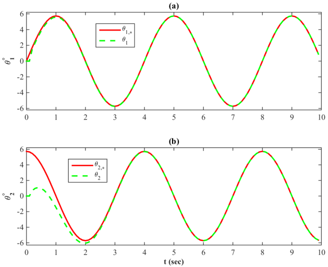
  3. The combined TLRM dynamics can be written as:

$$M(\theta)\ddot{\theta} + V(\theta, \dot{\theta}) + G(\theta) + F(\dot{\theta}) = \tau$$

- **Torque Disturbances**
  1. An external torque disturbance is introduced into the system after a duration of 5 seconds
  2. It is modelled as a sinusoidal signal with a frequency of 2π rad/sec
  3. The amplitude of the disturbance is taken to be 20% of the torque (τ) input

$$\tau_d = \begin{bmatrix} 0.2\tau_1 \sin 2\pi t \\ 0.2\tau_2 \sin 2\pi t \end{bmatrix} \tag{9}$$

Simulation Results with PD controller



(a) No uncertainties

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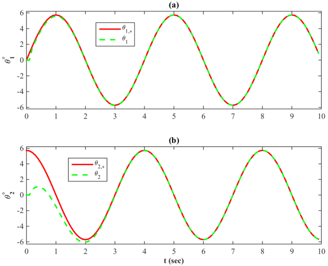

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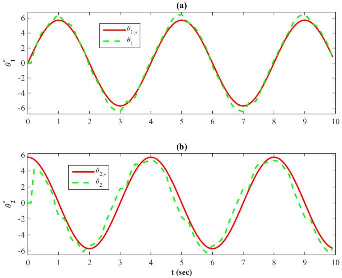

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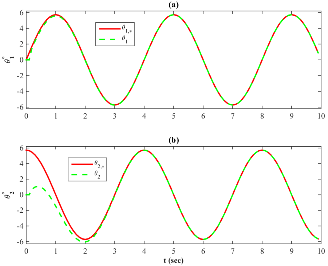

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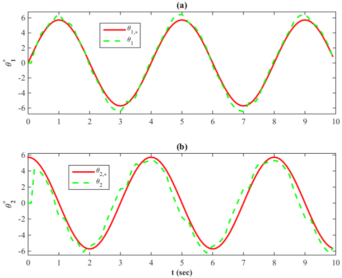

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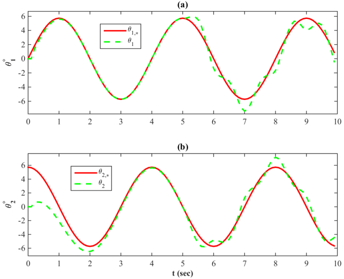
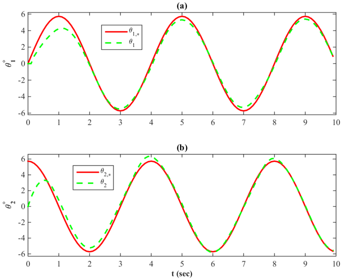


(c) With torque disturbances

Figure: Tracking performance of PD controller

Simulation Results with DDPG controller



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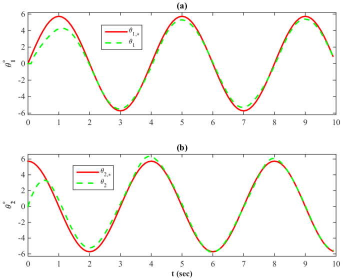

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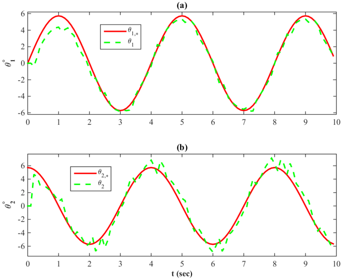

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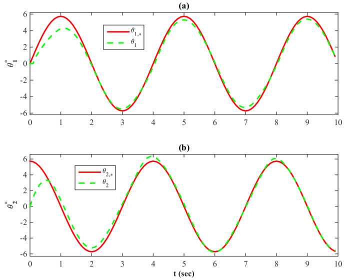

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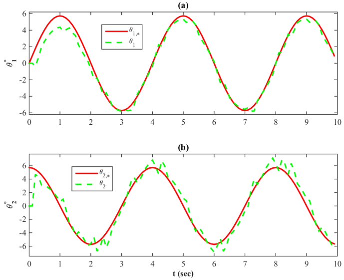

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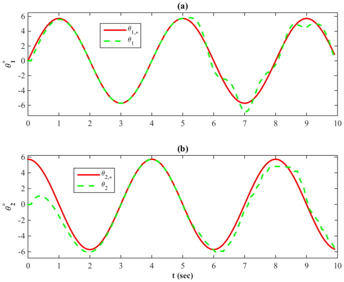

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Figure: Tracking performance of DDPG controller

Results

Table: Performance Comparison

Uncertainty	Angle	PD		DDPG	
		MSE	VAF	MSE	VAF
None	θ_1	0.399	97.493	0.581	96.726
	θ_2	1.940	89.798	0.830	94.970
Friction $F(\dot{\theta})$	θ_1	0.765	95.199	0.763	96.101
	θ_2	2.522	85.232	0.886	94.604
Torque τ_d	θ_1	0.793	95.161	0.668	95.798
	θ_2	2.744	84.963	1.855	90.635

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    3. comparison with several other RL algorithms

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