EXPLORACIÓN DEL DDPG TD3: UN ENFOQUE CONTINUO EN EL APRENDIZAJE POR REFUERZO

"Un Viaje a Través del Twin Delayed Deep Deterministic Policy Gradient y su Aplicación en Ambientes Desafiantes: HumanoidBulletEnv-v0"

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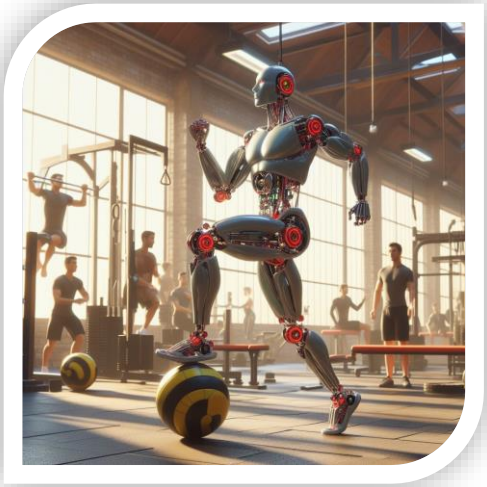
INTRODUCCIÓN



1. *Introducción*
2. *TD3: Twin Delayed DDPG*
3. *Implementación*
4. *Resultados*
5. *Conclusiones y Discusión*

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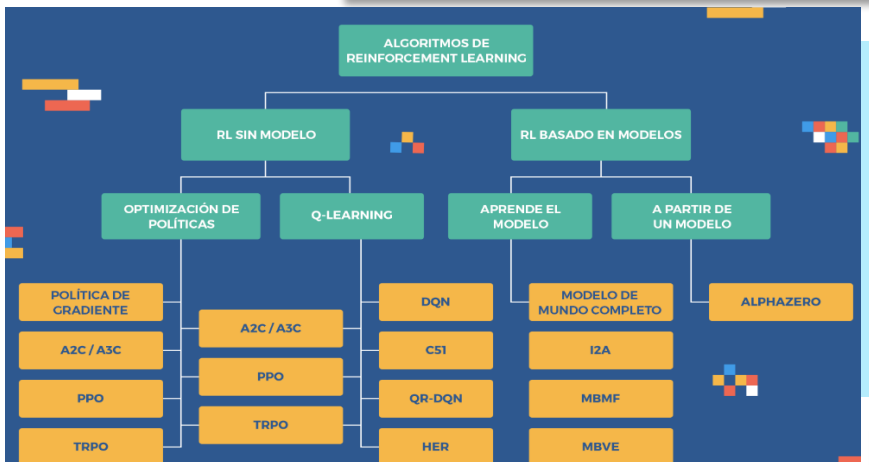
Introducción: RL- GYM

DDPG TD3: Gradiente Política Determinista de doble retardo



Diferencias Temporales (TD)
Vs Programación dinámica (PD):

Actualización valores Q
Optimización Política (∏)
No requiere modelo completo del entorno

❑ Estado

- *Posición, velocidad y orientación del cuerpo del humanoide*

❑ Entorno: *PyBullet y Gym*

- ***HumanoidBulletEnv-v0*** *:Simulador físico 3D*
- *Aprenda a caminar de manera eficiente y sin caerse.*

❑ Acciones

- ***Acciones continuas*** *(fuerzas aplicadas a las articulaciones)*

❑ Recompensa:

- *Mantenerse de pie*
- *Progresión hacia delante*
- *Eficiencia energética*

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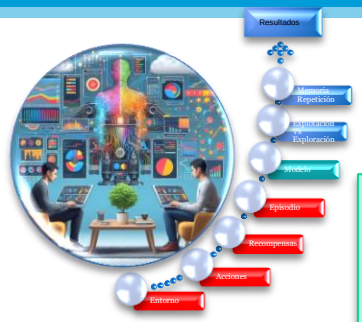
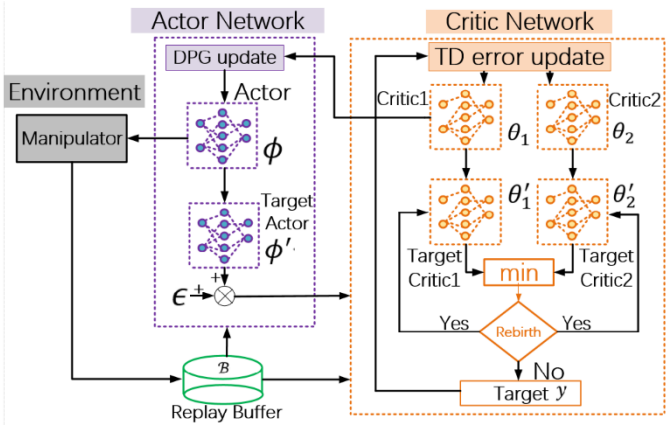


Introducción: RL- GYM

Deep Q-learning no es aplicable en el caso de acciones continúas

DDPG TD3



- ❑ **Actor Target + Actor Modl:**
  - ✓ **2 Capas ocultas + 2 Relu +Tanh**
- ❑ **2 Critic Target + 2 Critic Model:**
  - ❑ **2 Capas Ocultas + 1 Relu**

Addressing Function Approximation Error in Actor-Critic Method.
https://arxiv.org/pdf/1802.09477.pdf

$$R_t = \sum_{i=t}^{T} \gamma^{i-t} r(s_i, a_i)$$

$$J(\phi) = \mathbb{E}_{s_i \sim p_\pi, a_i \sim \pi}[R_0]$$

$$\nabla_\phi J(\phi) = \mathbb{E}_{s \sim p_\pi}\left[\nabla_a Q^\pi(s,a)|_{a=\pi(s)} \nabla_\phi \pi_\phi(s)\right]$$

$$\phi_{t+1} = \phi_t + \alpha \nabla_\phi J(\pi_\phi)|_{\phi_t}$$

ReplayBuffer

(s_1, s'_1, a_1, r_1)	(s_2, s'_2, a_2, r_2)	(s_3, s'_3, a_3, r_3)	(s_4, s'_4, a_4, r_4)	…

TD3: Twin Delayed DDPG

2 Críticos (M Vs T) + 1 Actor (M Vs T)

Algorithm 1 Twin Delayed DDPG

Input: initial policy parameters θ, Q-function parameters ϕ_1, ϕ_2, empty replay buffer $\mathcal{D}$
Set target parameters equal to main parameters $\theta_{\text{targ}} \leftarrow \theta$, $\phi_{\text{targ},1} \leftarrow \phi_1$, $\phi_{\text{targ},2} \leftarrow \phi_2$
repeat
  Observe state s and select action $a = \text{clip}(\mu_\theta(s) + \epsilon, a_{Low}, a_{High})$, where $\epsilon \sim \mathcal{N}$
  Execute a in the environment
  Observe next state s', reward r, and done signal d to indicate whether s' is terminal
  Store (s, a, r, s', d) in replay buffer $\mathcal{D}$
  If s' is terminal, reset environment state.
  if it's time to update **then**
    for j in range(however many updates) **do**
      Randomly sample a batch of transitions, $N = \{(s, a, r, s', d)\}$ from $\mathcal{D}$
      Compute target actions

$$a'(s') = \text{clip}\left(\mu_{\theta_{\text{targ}}}(s') + \text{clip}(\epsilon, -c, c), a_{Low}, a_{High}\right), \quad \epsilon \sim \mathcal{N}(0, \sigma)$$

      Compute targets

$$Q_{\phi}(r, s', d) = r + \gamma(1 - d) \min_{i=1,2} Q_{\phi_{\text{targ},i}}(s', a'(s'))$$

      Update Q-functions by one step of gradient descent using

$$\nabla_{\phi_i} \frac{1}{|N|} \sum_{(s,a,r,s',d) \in N} (Q_{\phi_i}(s, a) - Q_{\phi}(r, s', d))^2 \qquad \text{for } i = 1, 2$$

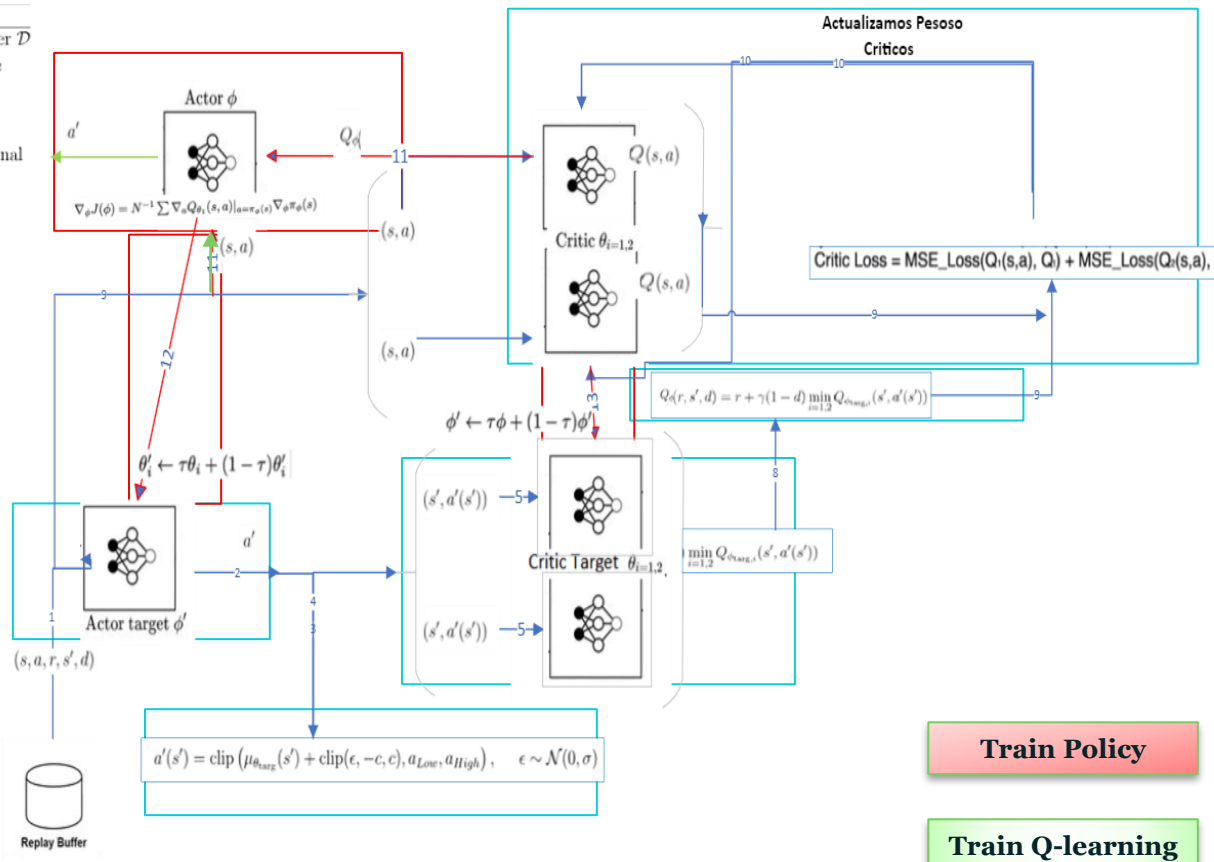
      if j mod `policy_delay` $= 0$ **then**
        Update policy by one step of gradient ascent using

$$\nabla_\phi J(\phi) = N^{-1} \sum \nabla_a Q_{\theta_1}(s, a)|_{a=\pi_\phi(s)} \nabla_\phi \pi_\phi(s)$$

        Update target networks with

$$\phi' \leftarrow \tau\phi + (1 - \tau)\phi' \qquad \text{for } i = 1, 2$$
$$\theta'_i \leftarrow \tau\theta_i + (1 - \tau)\theta'_i$$

      end if
    end for
  end if
until convergence



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Implementación: Train

Métodos de regularización

Discovery Vs Applicaction

- EGreedyPolicy: (AdaptiveEGreedyPolicy)
- AdaptiveBalancedPolicy
- AdaptiveHybridPolicy
- Reward-proximity Exploration

Noise Action

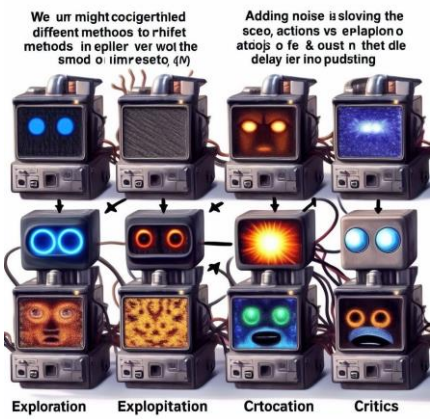
- Exploración
- Explotación (decaimiento)

Replay Memory

- Simple
- Simple PrioritizedReplayBuffer
- PrioritizedReplayBuffer
- ReplayBufferPos

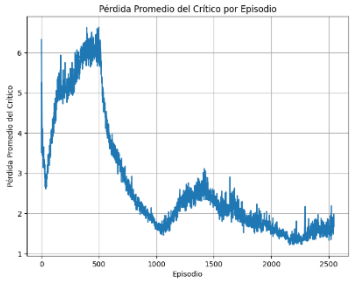
Dual Update Delay

- Cada dos pasos

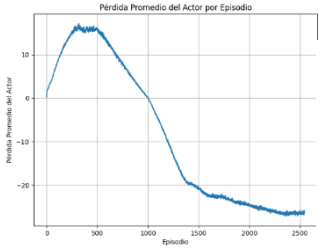


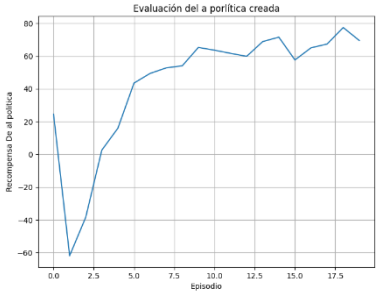
Resultados: Evaluación (I)

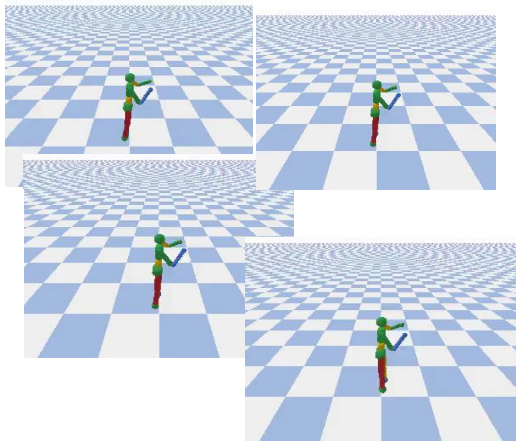
Explotación - Explotación



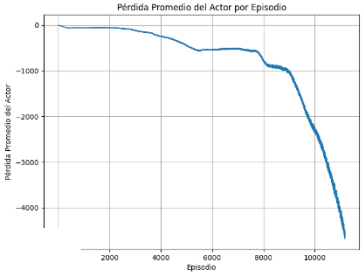
AdaptiveBalancedPolicy

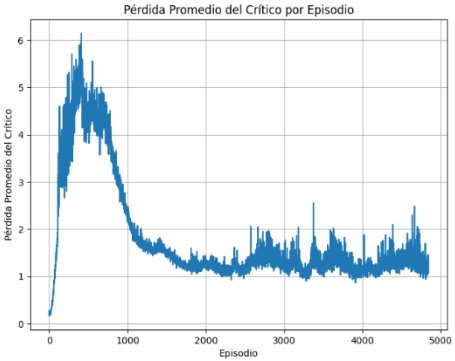


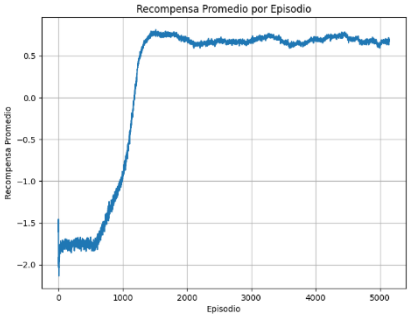


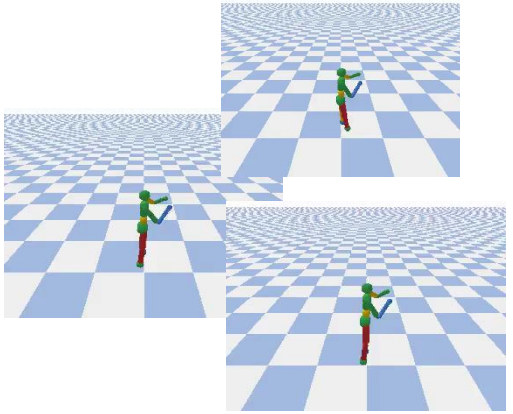


Reward-proximity Exploration



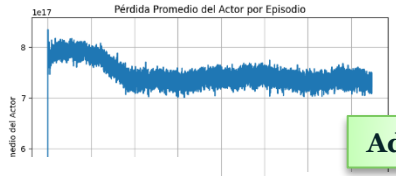




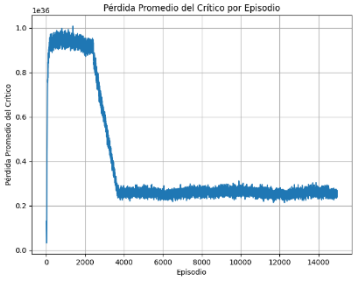


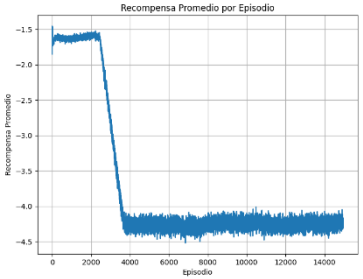
Resultados: Evaluación (II)

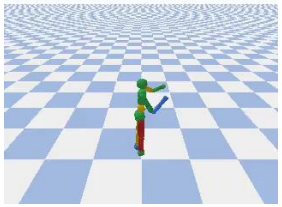
Explotación - Explotación

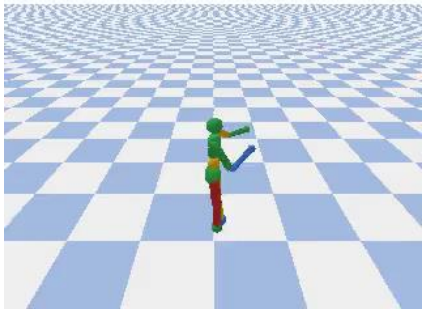


AdaptiveHybridPolicy

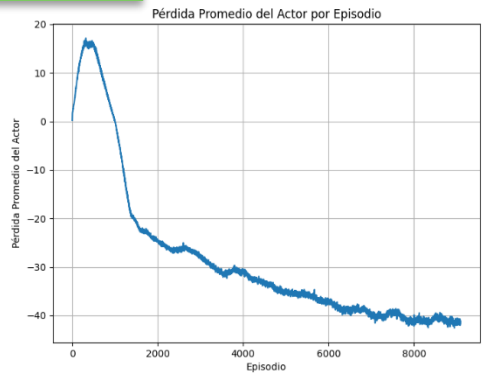


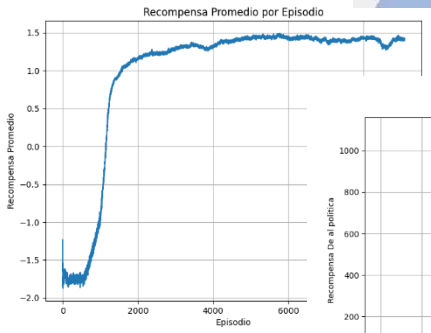


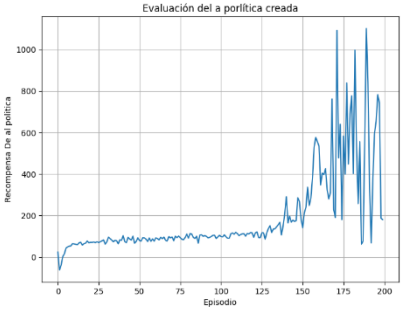


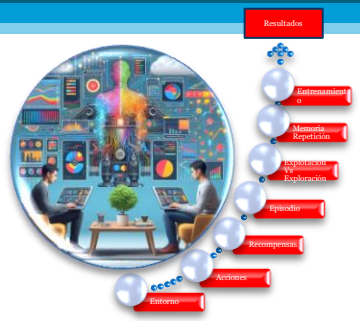


EGreedyPolicy





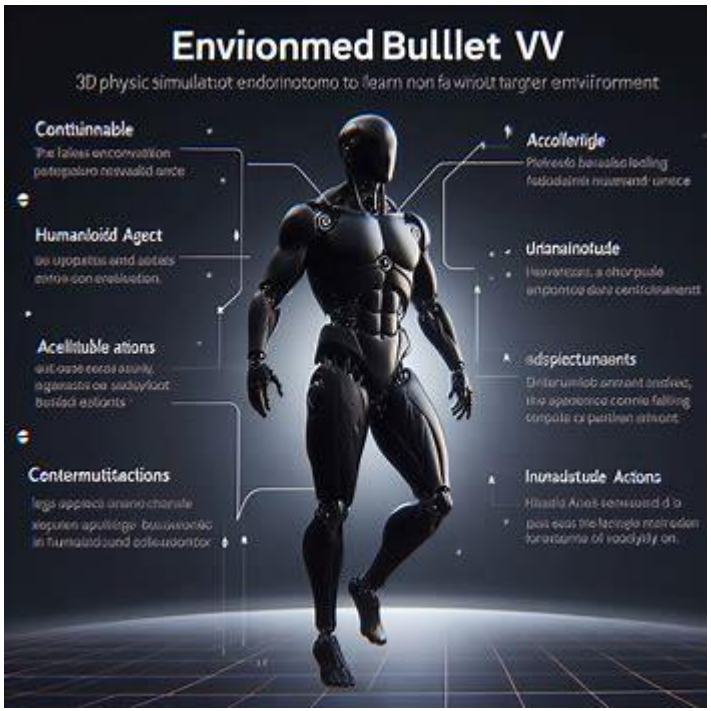




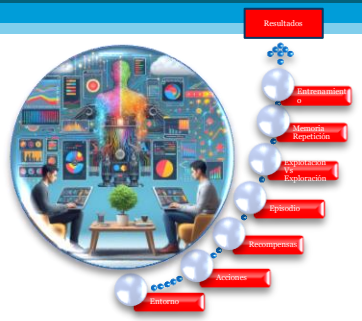
Conclusión: Modelo RL

Elevada Cantidad Pasos // Inestabilidad

Al evaluar la política: Se experimentan episodios en los que parece que el agente no está entrenado y su rendimiento es pobre:



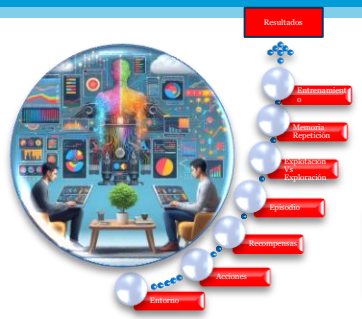
- ✓ Convergencia a acciones subóptimas
- ✓ Exploración insuficiente
- ✓ Convergencia insuficiente
- ✓ Hiperparámetros incorrectos
- ✓ Problema intrínseco de la tarea



Discusión: Modelo RL

Elevada Cantidad Pasos // Inestabilidad

- Llegar a entrenar bien el actor - 2 críticos para que el humanoide ande decentemente es un dolor de cabeza.
- Necesidad de regulación para evitar estancamientos y sobrestimación (los críticos)
- Muy sensible a los hiperparámetros y las acciones a realizar .
- La adición de ruido N(0,σ') mejora el algoritmo frente a búsqueda aleatoria entorno real



Aplicación: Modelo RL

DDPG TD3 4.670 resultados

Multiagent Copilot Approach for Shared Autonomy between Human EEG and TD3 Deep Reinforcement Learning
https://www.semanticscholar.org/reader/836ccd5130525103c150336ae699bb36ceb86e94

The Control Method of Twin Delayed Deep Deterministic Policy Gradient with Rebirth Mechanism to Multi-DOF Manipulator
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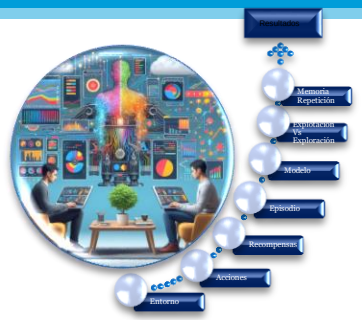

THE-END

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Kim, Myeongseop & Han, Dong-Ki & Park, Jae-Han & Kim, Jung-Su. (2020). Motion Planning of Robot Manipulators for a Smoother Path Using a Twin Delayed Deep Deterministic Policy Gradient with Hindsight Experience Replay

Applied Sciences. 10. 575. 10.3390/app10020575.

Kim, Myeongseop & Han, Dong-Ki & Park, Jae-Han & Kim, Jung-Su. (2020). Motion Planning of Robot Manipulators for a Smoother Path Using a Twin Delayed Deep Deterministic Policy Gradient with Hindsight Experience Replay

Applied Sciences. 10. 575. 10.3390/app10020575.

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