상용 시뮬레이터 기반 차량 동역학을 고려한 강화학습 환경 구축

Development of Simulation Environment for Vehicle Dynamics-based Reinforcement Learning Using CarMaker Simulator

팀 명	TOCA
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지도 교수	Prof. Han, Kyoungseok

1. Motivation

- With the rapid growth of the autonomous driving industry, research is underway on related driving and behavioral control algorithms.
- IPG CarMaker is a simulation program capable of realistic driving environment emulation.
- The TD3 reinforcement learning algorithm is well-suited for problems in continuous action spaces, such as vehicle speed and steering angle.

2. Project Overview

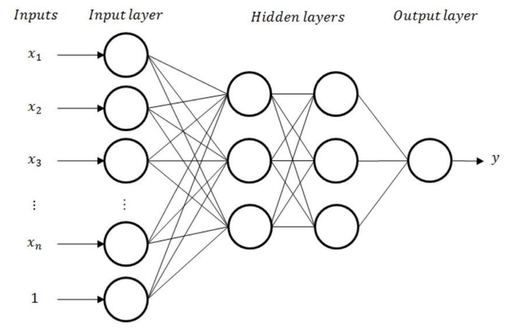
- **TD3 Algorithm**

Algorithm 1 TD3

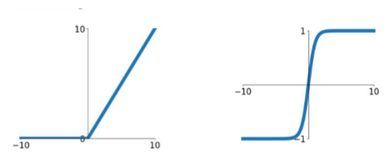
Initialize critic networks Q_{θ_1}, Q_{θ_2}, and actor network π_ϕ with random parameters θ_1, θ_2, ϕ
Initialize target networks $\theta'_1 \leftarrow \theta_1$, $\theta'_2 \leftarrow \theta_2$, $\phi' \leftarrow \phi$
Initialize replay buffer $\mathcal{B}$
for $t = 1$ **to** T **do**
  Select action with exploration noise $a \sim \pi(s) + \epsilon$, $\epsilon \sim \mathcal{N}(0, \sigma)$ and observe reward r and new state s'
  Store transition tuple (s, a, r, s') in $\mathcal{B}$

  Sample mini-batch of N transitions (s, a, r, s') from $\mathcal{B}$
  $\tilde{a} \leftarrow \pi_{\phi'}(s) + \epsilon, \quad \epsilon \sim \text{clip}(\mathcal{N}(0, \tilde{\sigma}), -c, c)$
  $y \leftarrow r + \gamma \min_{i=1,2} Q_{\theta'_i}(s', \tilde{a})$
  Update critics $\theta_i \leftarrow \min_{\theta_i} N^{-1} \sum (y - Q_{\theta_i}(s, a))^2$
  if t mod d **then**
    Update ϕ by the deterministic policy gradient:
    $\nabla_\phi J(\phi) = N^{-1} \sum \nabla_a Q_{\theta_1}(s, a)|_{a=\pi_\phi(s)} \nabla_\phi \pi_\phi(s)$
    Update target networks:
    $\theta'_i \leftarrow \tau\theta_i + (1 - \tau)\theta'_i$
    $\phi' \leftarrow \tau\phi + (1 - \tau)\phi'$
  end if
end for

<TD3 Algorithm>



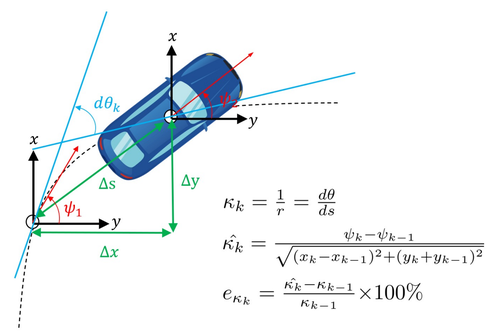
<MLP Structure>



<Activation Function – ReLu, tanh>

- TD3, a member of the Actor-Critic family, adopts the DDPG-based architecture, making it suitable for application in continuous action spaces.
- TD3 comprises two independent Critic neural networks (MLP), utilizing the smaller value between the two calculated value estimates from each network as the target for Q-learning. This approach effectively addresses overestimation and variance issues.

- **RL Environment**

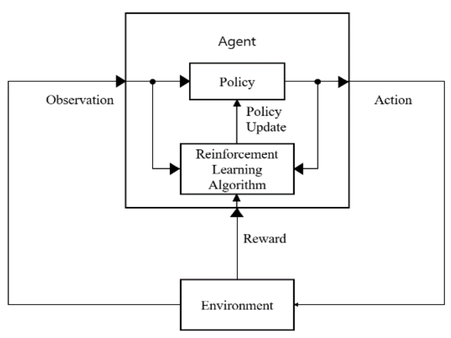


$$\kappa_k = \frac{1}{r} = \frac{d\theta}{ds}$$

$$\hat{\kappa_k} = \frac{\psi_k - \psi_{k-1}}{\sqrt{(x_k - x_{k-1})^2 + (y_k + y_{k-1})^2}}$$

$$e_{\kappa_k} = \frac{\hat{\kappa_k} - \kappa_{k-1}}{\kappa_{k-1}} \times 100\%$$

< Vehicle dynamics>



< RL Agent-Environment Interaction >

$$s(\mathrm{k}) = [x(k), \mathrm{y}(\mathrm{k}), v_x(\mathrm{k}), v_y(\mathrm{k}), \tau(\mathrm{k}), \delta(\mathrm{k}), \psi(\mathrm{k}), \ \mathrm{y}^*(\mathrm{k}), \kappa_\mathrm{p}(\mathrm{k}), \mathrm{s}(\mathrm{k}-1)]^\mathrm{T}$$

$$\vec{a} = [\delta, \ \tau]^T$$

$$w_1 = 0.5, w_2 = 0.1, w_3 = 0.2, w_4 = 0.2$$

$$\mathrm{r}_{tot} = \mathrm{r}_{\mathrm{y}^*} + \mathrm{r}_\mathrm{s} + \mathrm{r}_{\mathrm{v_x}} + \mathrm{r}_{\kappa_\mathrm{t}} + \mathrm{r}_\mathrm{T}$$

$$\mathrm{B}(x) = \frac{1}{1 + \left|\frac{x - c}{a}\right|^{2b}}$$

$$\mathrm{r}_{\mathrm{y}^*}(y^*) = w_1 \frac{10}{1 + \left|\frac{y^* + 1.7}{0.4}\right|^{2(7.5)}}$$

$$r_s(s_k) = w_2(s_k - s_{k-1})$$

$$\mathrm{r}_{\mathrm{v_x}}(v_x) = w_3 \frac{10}{1 + \left|\frac{v_x - 15}{4}\right|^{2(2)}}$$

$$r_{\kappa_\mathrm{k}} = \begin{cases} w_4(10) & \mathrm{e}_{\kappa_\mathrm{k}} < 15\% \\ w_4(-10) & else \end{cases}$$

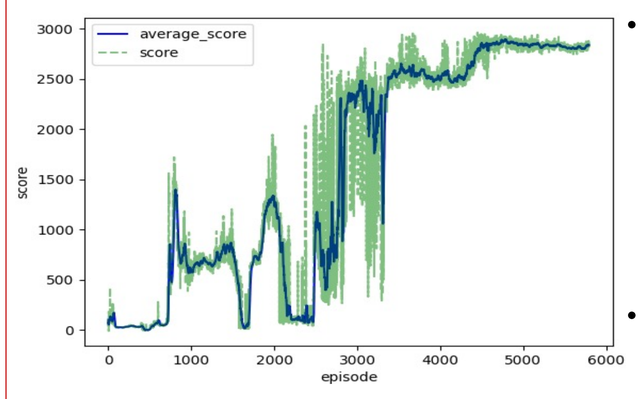
$$r_T = -3$$

$$y^* > 3m \ \ or \ \ y^* < 0.1m$$

$$\psi > 1.4rad$$

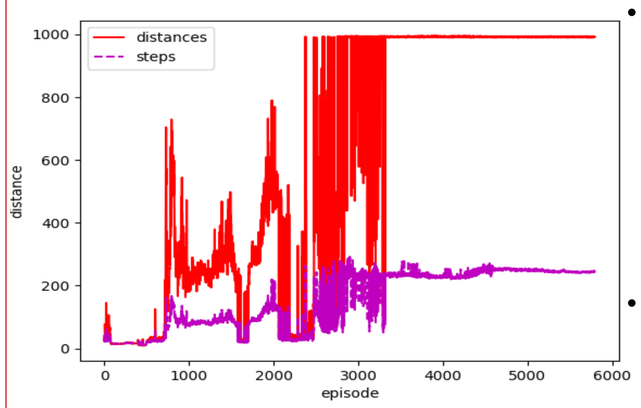
$$v < 4m/s$$

3. Results



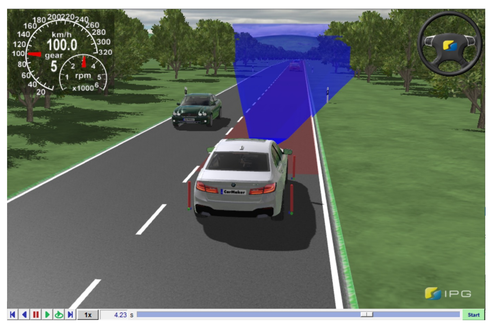
< Reward / Average Reward>

- Our investigation reveals a consistent increase in the Score and Step metrics per episode as learning progresses. This observation indicates the effectiveness of the policy learned through the generated reward function.
- With approximately 6000 episodes conducted, the model reliably completes the given road length of 1000m after a certain number of episodes.



< Distance / Time Step >

- After reaching the 1000m road length, the Score per episode exhibits a gradual increase to converge, signifying the completion of learning and stable lane tracking at the center.
- The trained model demonstrates the capability to follow the center of the lane reliably across diverse road configurations.



<IPG Carmaker driving simulation>

4. Expected Outcomes

- This research presents the implementation of a learning-based autonomous driving model in the commercial simulator environment, IPG Carmaker.
- Learning-based autonomous algorithms are scarcely commercialized due to challenges in acquiring driving data and the inherent risks involved, hindering performance assessment in real driving environments.
- Reinforcement learning empowers the driving system to make real-time decisions, monitor the surroundings, and choose optimal actions. Moreover, the system autonomously learns suitable responses to new situations.
- Thus, the reinforcement learning environment developed in this study holds the potential for versatile applications across diverse scenarios.

5. Future Work

- This study applied reinforcement learning to a straightforward road model. Future research aims to implement reinforcement learning models in more complex scenarios, incorporating constraints like other vehicles and traffic signals on intricate paths.
- While this study focused on controlling a single vehicle, future work involves leveraging ROS communication to train multiple vehicles simultaneously in diverse situations or exploring alternative control methods such as platoon driving.

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지도 교수	한경석

1. 과제 선정 배경 및 필요성

- 최근 자율주행 자동차 산업이 급격히 성장함에 따라 관련된 주행 및 행동제어 알고리즘이 연구되고 있다.
- IPG CarMaker는 현실적인 주행환경 모사가 가능한 시뮬레이션 프로그램이다.
- TD3 강화학습 알고리즘은 차량의 속도, 조향각과 같은 연속적인 행동공간에서의 문제에 적용하기 적합하다.

2. 수행내용

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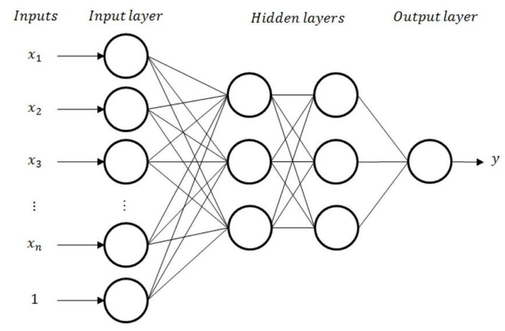
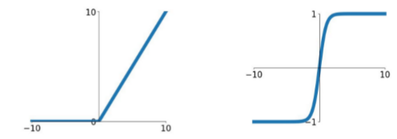
<TD3 Algorithm>



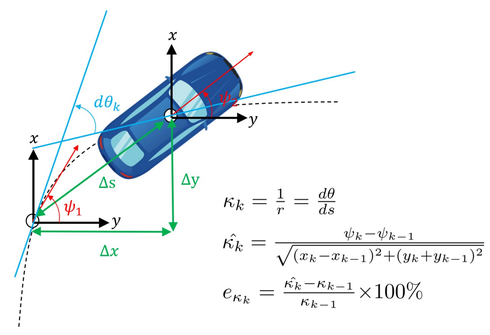
<MLP Structure>



<Activation Function – ReLu, tanh>

- Actor-Critic 계열의 TD3는 DDPG기반 구조를 가지고 있어 연속적인 행동공간에 적용할 수 있다.
- TD3는 2개의 독립적인 Critic신경망(MLP)으로 구성되며 각각의 신경망에서 계산된 두 개의 가치 추산치에서 더 작은 값을 Q-learning의 Target으로 이용함으로써 과도한 가치 추산 문제와 분산 문제를 해결하였다.

- **RL Environment**



< Vehicle dynamics>

$$s(\mathrm{k}) = [x(k), \mathrm{y}(\mathrm{k}), v_x(\mathrm{k}), v_y(\mathrm{k}), \tau(\mathrm{k}), \delta(\mathrm{k}), \psi(\mathrm{k}), \ \mathrm{y}^*(\mathrm{k}), \kappa_\mathrm{p}(\mathrm{k}), \mathrm{s}(\mathrm{k}-1)]^\mathrm{T}$$

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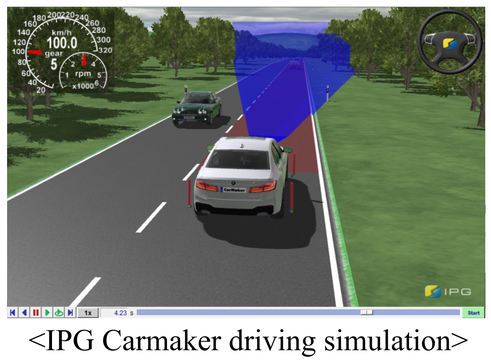
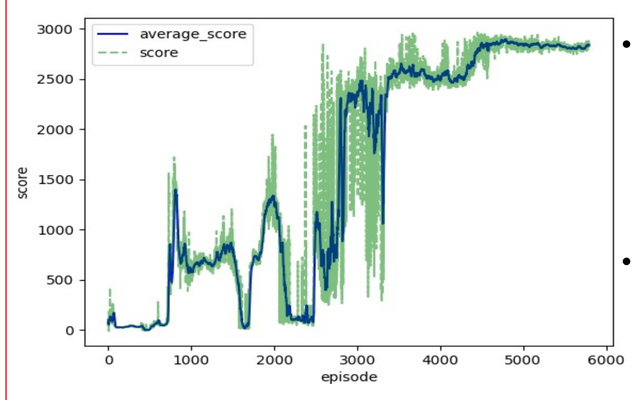


< RL Agent-Environment Interaction >

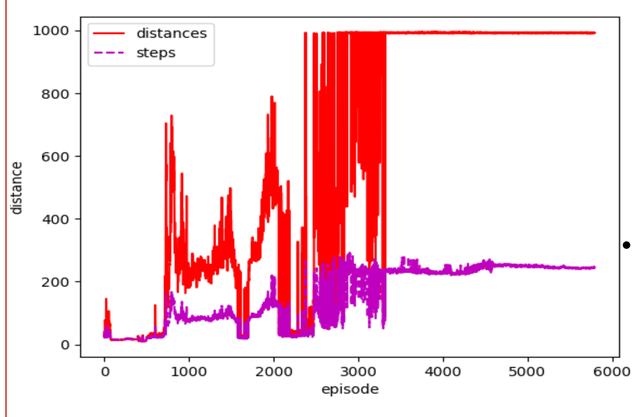
<IPG Carmaker driving simulation>

3. 최종 결과물



< Reward / Average Reward>

- 학습이 진행됨에 따라 에피소드당 Score, Step이 증가함을 확인할 수 있다. 이를 통해 만들어진 보상함수로 학습된 정책이 효과를 보인다는 것을 알 수 있다.
- 에피소드는 약 6000번 수행되었으며, 에피소드가 어느 정도 수행된 후 주어진 도로의 길이인 1000m까지 안정적으로 완주하는 것을 확인할 수 있다.



< Distance / Time Step >

- 도로 길이인 1000m까지 완주한 이후에도 에피소드당 Score는 점진적으로 증가하다가 수렴하게 되는데, 이를 통해 학습이 완료됨과 차선의 중앙을 안정적으로 추종함을 확인할 수 있다.
- 학습을 통해 만들어진 모델은 다양한 형태의 도로에서 차선 중앙을 추종하며 주행할 수 있을 것으로 판단된다.

4. 기대효과

- 본 연구에서는 상용 시뮬레이터인 IPG Carmaker 환경에서 학습기반의 주행모델을 구현하였다.
- 학습을 기반으로 한 자율주행 알고리즘은 상용화 된 것이 거의 없다. 주행 데이터를 얻기 힘들고 통제를 벗어날 경우 위험요소가 많아 실제 주행 환경에 적용하여 학습 성능을 측정하기에 어려움이 있기 때문이다.
- 강화학습은 주행 시스템이 실시간으로 의사결정을 내릴 수 있는 능력을 제공한다. 주행 시스템은 주변 환경을 모니터링하고, 현재 상황에 맞는 최적의 행동을 선택한다. 또한 새로운 상황에 대한 적절한 행동을 스스로 학습한다.
- 따라서 본 연구를 통해 구현된 강화학습 환경은 다양한 경우에 응용될 수 있을 것으로 기대된다.

5. 향후 계획

- 본 연구에서는 단순한 도로 모델에서 강화학습을 적용하였다. 향후에는 더욱 복잡한 경로에서 상대 차량, 신호등과 같은 여러 제약이 있는 조건으로 강화학습 모델을 구현하고자 한다.
- 본 연구에서는 하나의 차량만을 제어할 수 있었으나, 향후 ROS통신 등을 이용하여 하나의 제어기로 여러 대의 차량을 동시에 다양한 상황에서 학습시키거나, 군집주행 등의 다른 방식의 제어를 해보고자 한다.