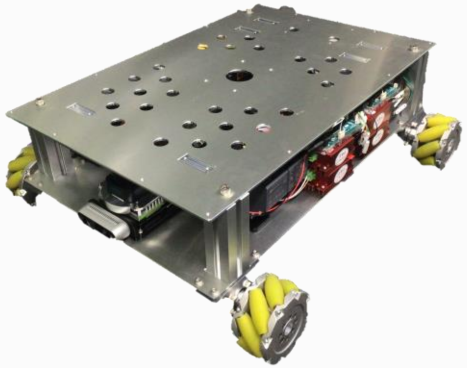
ML in Control

001 Domain : Control Engineering

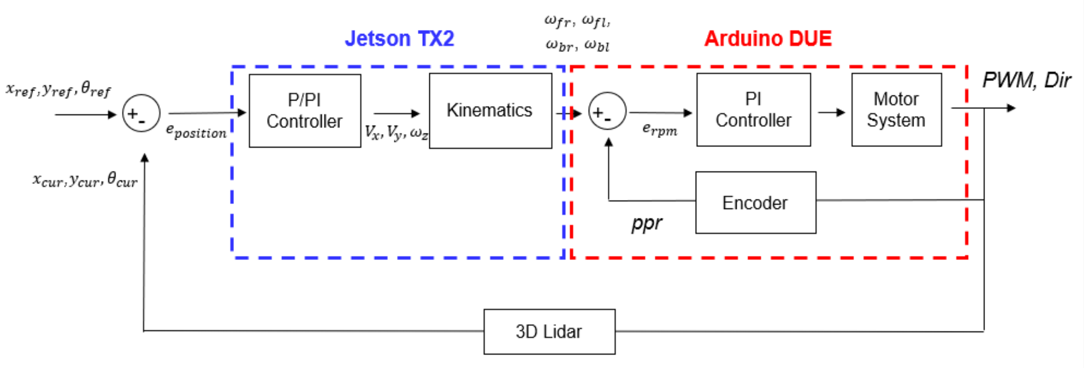
Autonomous Driving for a robot, a car

001 Domain : Control Engineering

2-Wheel Robot



4-Wheel Robot



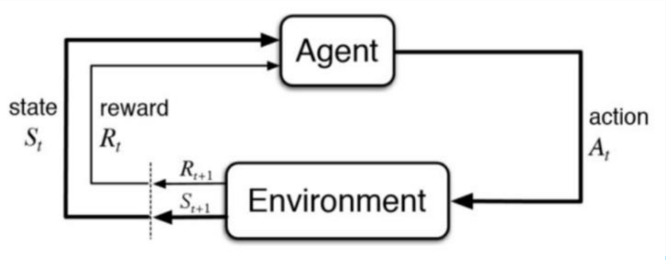
4-Wheel Robot Control Diagram

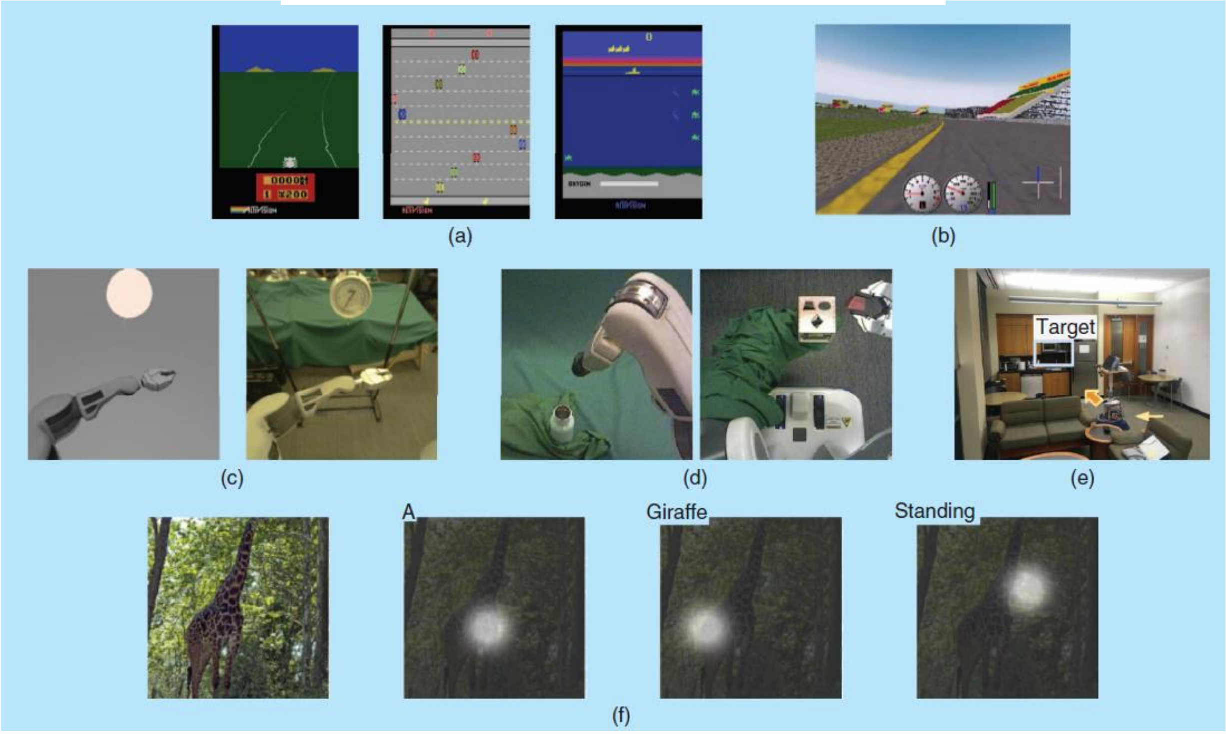
1. 자동차 부품 연구개발
2. 로봇 전장 설계 및 하위제어기 연구개발

Why Feedback?
uncertainty, Instability, Disturbance, Efficient

인공지능은 제어에 어떻게 활용될 것인가?

Thesis : RL(Reinforcement Learning)





1. 사용되는 곳 :

- 게임의 기준 시험
- 자동차 시뮬레이터(자율주행 연구개발)
- 로봇 시뮬레이션(실제 자료와 비슷하게 구현)
- 로봇 팔로 딱 맞는 조각 조립하기
- 빌딩 자율주행 로봇 네비게이션 학습
- 기린 사진 학습

2. 학습전략 : Deep Reinforcement Learning

3. 네트워크 : DQN(Deep Q-Network)

002 Thesis : RL(Reinforcement Learning)

Ref.	Learning Strategy	Network	Inputs	Outputs	Pros	Cons
[94]	Fuzzy reinforcement learning	Feedforward network with one hidden layer	Relative distance, relative speed, previous control input	Throttle angle, brake torque	Model-free, continuous action values	Single term reward function
[23]	Reinforcement learning	Feedforward network with one hidden layer	Time headway, headway derivative	Accelerate, brake, or no-op	Maintains a safe distance	Oscillatory acceleration behavior, no term for comfort in reward function
[95]	Reinforcement learning	Actor-Critic Network	Velocity, velocity tracking error, acceleration error, expected acceleration	Gas and brake commands	Learns from minimal training data	Noisy behavior of the steering signal
[98]	Reinforcement learning	Feedforward network with five hidden layers	Vehicle velocity, relative position of the pedestrian for past five time steps	Discretized deceleration actions	Reliably avoids collisions	Only considers collision avoidance with pedestrians
[96]	Reinforcement learning	Feedforward network with one hidden layer	Relative distance, relative velocity, relative acceleration (normalized)	Desired acceleration	Provides smooth driving styles, learns personal driving styles	No methods for preventing learning of bad habits from human drivers
[97]	Reinforcement learning	Actor-Critic Network	Relative distance, host velocity, relative velocity, host acceleration	Desired acceleration	Performs well in a variety of scenarios, safety and comfort considered, learns personal driving styles	Adapting unsafe driver habits could degrade safety
[22]	Supervised reinforcement learning	Actor-Critic Network	Relative distance, relative velocity	Desired acceleration	Pre-training by supervised learning accelerates learning process and helps guarantee convergence, performs well in critical scenarios	Requires supervision to converge, driving comfort not considered

1. 사용되는 곳 : 자율주행 종방향(Longitudinal) 제어

2.학습 전략 : Fuzzy Reinforcement Learning / Reinforcement Learning

3. 네트워크 : FN, Actor-Critic Network

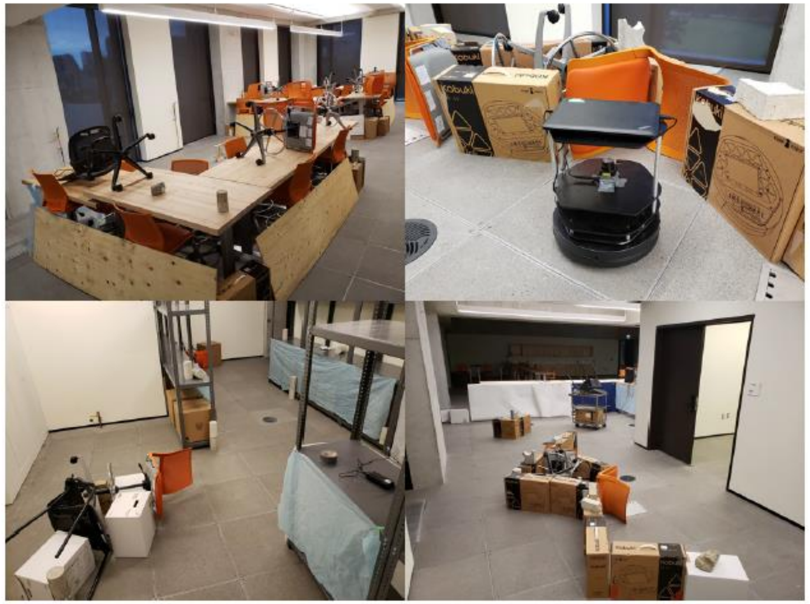
002 Thesis : DL(Deep Learning)

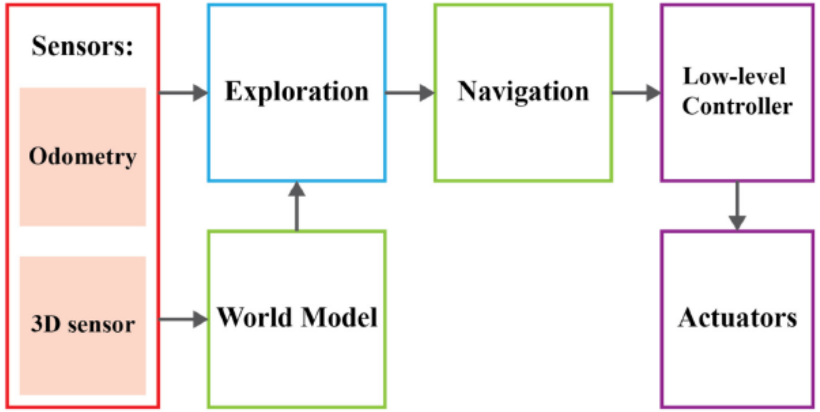
Ref.	Learning Strategy	Network	Inputs	Outputs	Pros	Cons
[83], [84]	Supervised learning	Feedforward network with one hidden layer	Camera image	Discretized steering angles	First promising results for neural network-based vehicle controllers	Simple network and discretized outputs degrade performance
[85]	Reinforcement Learning	Feedforward network with one hidden layer	Camera image	Discretized steering angles	Supports online learning	Simple network and discretized outputs degrade performance
[86]	Supervised learning	six-layer CNN	Camera image	Steering angle	Robust to environmental diversity	Large errors, trained and tested on a sub-scale vehicle model
[87]	Supervised learning	nine-layer CNN	Camera image	Steering angle values	High level of autonomy during field test	Only considers lane following, occasionally requires interventions by the driver
[45]	Supervised learning	eight-layer CNN	Simulated camera image	Steering angle values	Learns from minimal training data	Oscillatory behavior of the steering signal
[88]	Supervised learning	CNN-RNN	Camera image	Steering angle values	Considers temporal dependencies	Instability of RNN training, No live testing

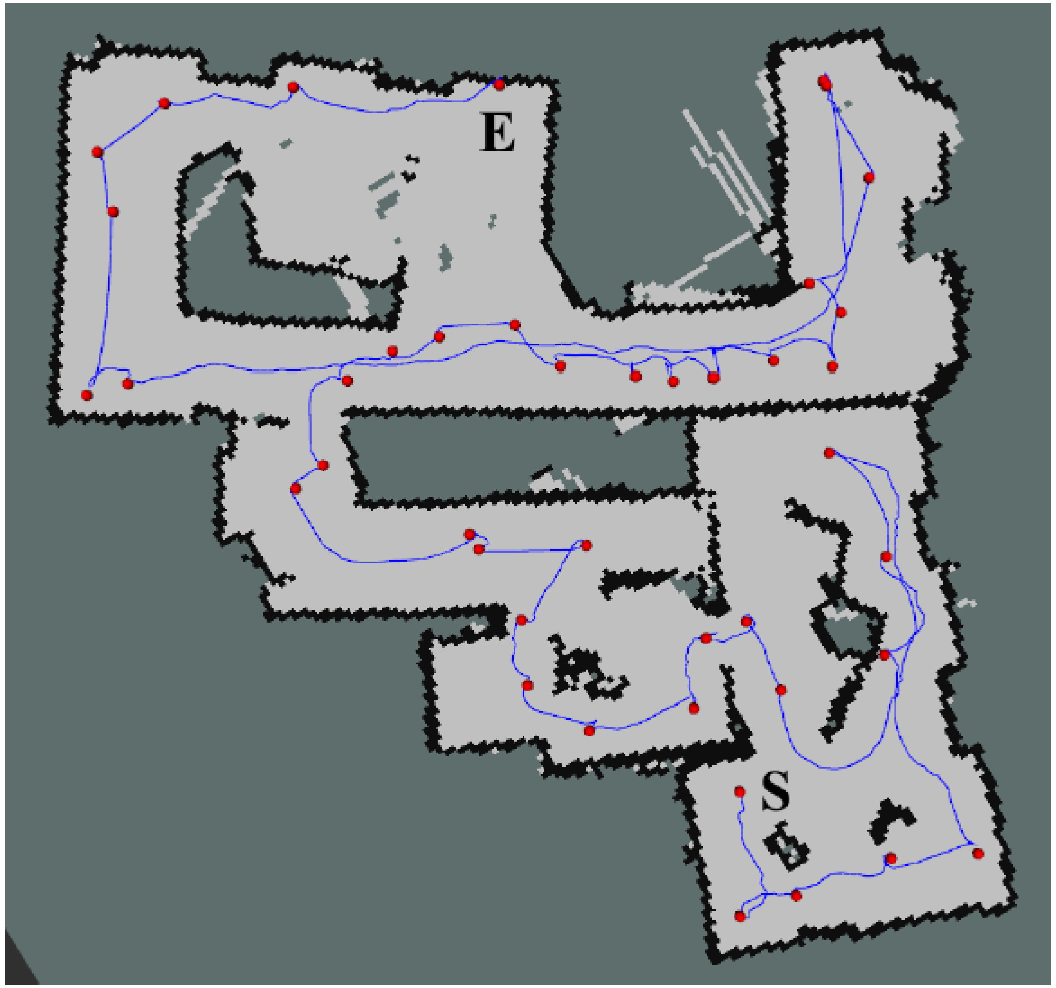
1. 사용되는 곳 : 자율주행 횡방향(Lateral) 제어
2. 학습 전략 : Supervised Learning / Reinforcement Learning
3. 네트워크 : CNN, RNN, FN(Feedforward Network)

002

Thesis : Applications – Mobile Robot Navigation

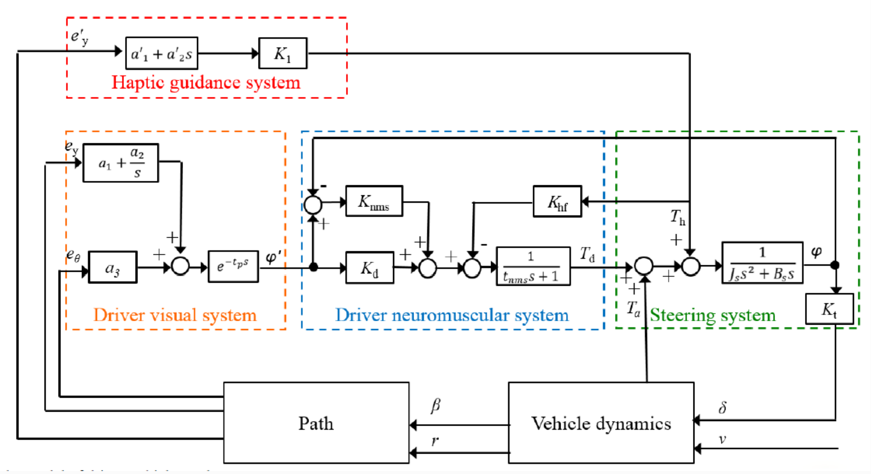


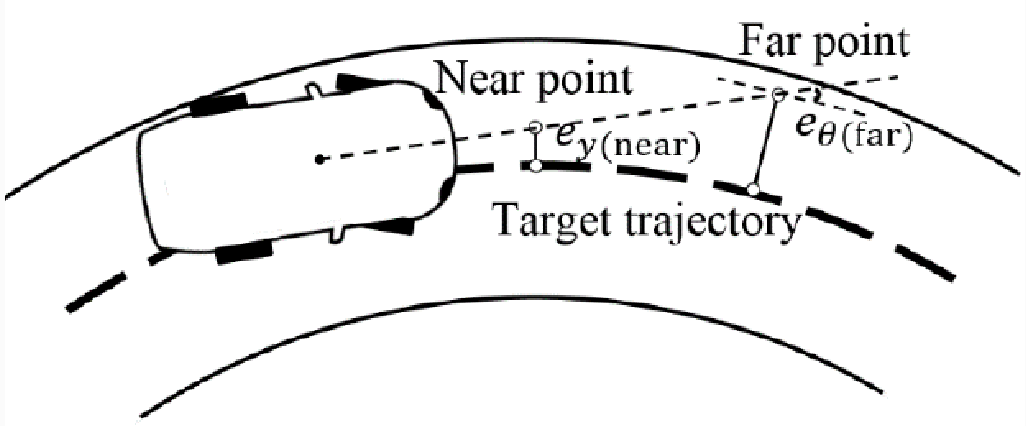


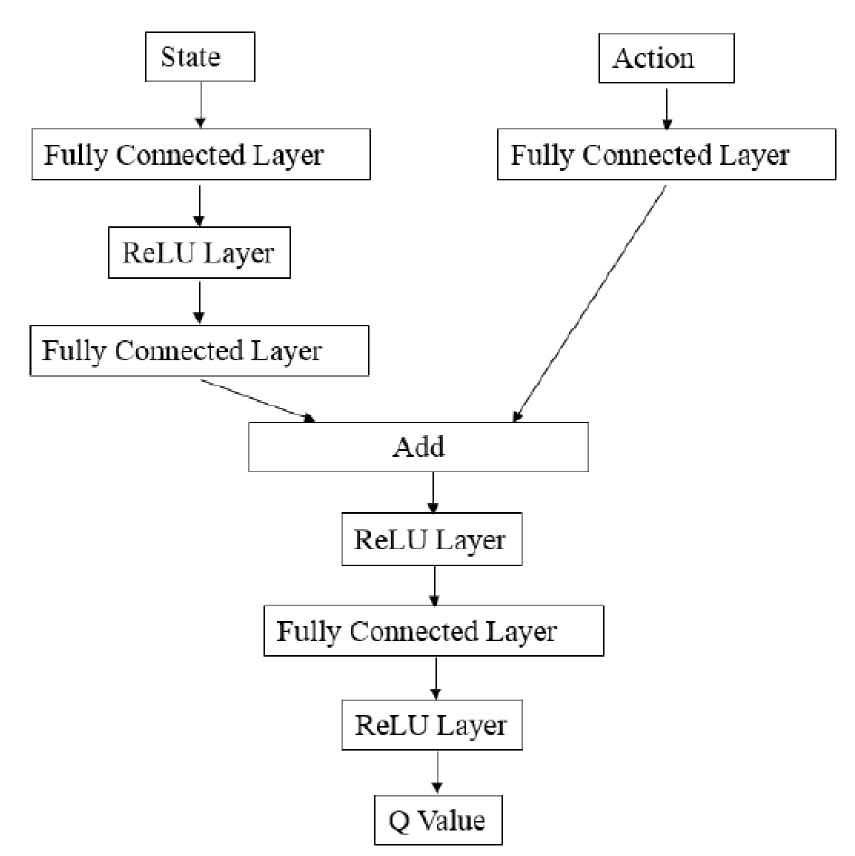


002

Thesis : Applications – Haptic Guidance System







003

Summary

Actor-Critic, FN, CNN, RNN

Network

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Robot, Trajectory Prediction, Nonlinear function

Applications

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Boundedness of weight, Real-time

Challenges

→ Reinforcement learning is a trend in control engineering.

004

Reference

[1] K. Arulkumaran, M. P. Deisenroth, M. Brundage and A. A. Bharath, "Deep Reinforcement Learning: A Brief Survey," in *IEEE Signal Processing Magazine*, vol. 34, no. 6, pp. 26-38, Nov. 2017, doi: 10.1109/MSP.2017.2743240.

[2] Sampo Kuutti; Saber Fallah; Richard Bowden; Phil Barber, *Deep Learning for Autonomous Vehicle Control: Algorithms, State-of-the-Art, and Future Prospects* , Morgan & Claypool, 2019, doi: 10.2200/S00932ED1V01Y201906AAT008.

[3] F. Niroui, K. Zhang, Z. Kashino and G. Nejat, "Deep Reinforcement Learning Robot for Search and Rescue Applications: Exploration in Unknown Cluttered Environments," in *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 610-617, April 2019, doi: 10.1109/LRA.2019.2891991.

[4] Z. Wang, Z. Yan and K. Nakano, "Comfort-oriented Haptic Guidance Steering via Deep Reinforcement Learning for Individualized Lane Keeping Assist," *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Bari, Italy, 2019, pp. 4283-4289, doi: 10.1109/SMC.2019.8914219.

[5] https://www.novatec-gmbh.de/en/blog/introduction-to-q-learning/