Autonomous Car Parking

CS7IS2 Project (2021/2022)

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Abstract. Motivation behind the work, high level description of the problem, how it was solved by the proposed algorithms.

Keywords: soft-actor-critic, behaviour cloning, evolutionary algorithm, parking

1 Introduction

The Autonomous Vehicle (AV) industry is one of the most active and promising area in the recent years with many ongoing research to make it fully autonomous [16]. The International Society of Automotive Engineers (SAE) proposed a six-degree autonomy scale with level 0 as no automation and level 5 as full automation without any human interventions [14]. The current level of autonomy scale achieved today is between level 2 and 3 requiring some assistance from the driver and limited to ideal conditions.

Car parking is challenging and disliked by most drivers due to time required searching for spaces, risk of scratching vehicle, safety of pedestrian, etc [1][7]. It requires the driver to estimate the space required for the car and manoeuvre it into available space by controlling the steering angle and accelerator. While in fact the traffic report statistics survery results found in 12 million traffic accidents, there are about 10,000 traffic accidents occurring in the parking lots with many more number of accidents not reported [18].

Most vehicles are parked 95% throughout the lifetime [3]. Parking is required by every driver and apply AV will greatly improve the quality of life and ease of drivers. It increases driving safety by utilising various sensors to understand the environment surround vehicle and park at the designated space avoid collisions due to lack of human experiences [18]. Other potential application for autonomous car parking is saving spaces in car parking lots by parking in an optimal grid resulting in a much efficient parking lot capable of more car [3].

The highway-env github repository[1] contains a collection of autonomous driving and tactical decision-making tasks environment [9]. The parking environment[2] is selected for the project which is a goal-conditioned continuous control task in a given space with a vehicle aiming to reach the destination point. The

[1] https://github.com/eleurent/highway-env
[2] id of "parking-v0"

parking environment uses a grid like layout similar to actual car parks. the vehicle requires input of the steering angle and accelerator. Policy based algorithm is commonly used for autonomous vehicles instead of value based algorithm due its large action decision requiring huge memory [15]. The selected algorithms to be investigated in the project are Soft-Actor-Critic (SAC) from the reinforcement learning family, behaviour cloning from the imitation family and evolutionary algorithm from the genetic population-based family.

2 Related Work

The autonomous vehicle control system consists of mission trajectory planning system generating path for vehicle to reach target, navigation system detecting environment and either moving or fixed target and trajectory tracking controller to navigate the vehicle accordingly [10]. Path planning problem is the main subject of most autonomous vehicle studies. Prior to path planning, the algorithm needs to know the state of the vehicle such as its position and direction. GPS is commonly used to deduce the state by using signals Line Of Sight (LOS) from positioning satellite but not possible in the context of indoor parking lots [5] and high-rise buildings [13]. Instead other data such as vision-based sensors and LiDAR sensors are used to monitor the state of vehicle [2]. The works related to autonomous car parking uses different inputs and types algorithm families, this section mainly focuses on selected algorithms mentioned in Section 1.

Behaviour Cloning (BC) is from the Imitation learning family which uses observations from the expert to learn [17]. In paper [13] trains a Recurrent Convolutional Network for autonomous driving in lane changing context by using BC to learn from human experts driving vehicles. The paper noted the ease of changing architecture when using BC technique and found that spatio-temporal properties worked well in dynamic environments. The huge advantage of BC algorithm is its end-to-end trainable architecture which uses supervised learning to learn policies from an expert by inferring expert's actions [4][6][11][13]. However the BC approach suffers from several limitations such as over-fitting and generalisation issue [4]. BC algorithm is a simple yet effective approach in the project and it can be used to learn the policies created from other algorithms selected in the project.

3 Problem Definition and Algorithm

Problem definition and algorithm

3.1 Soft-Actor-Critic Algorithm

3.2 Behaviour Cloning Algorithm

Behaviour Cloning (BC) generates trajectory by learning policy from direct mapping of states to actions without recovering reward function of the expert [12].

$$\tau^d = \pi(s) \tag{1}$$

$$\upsilon_t = \pi(x_t) \tag{2}$$

Equation (1) is the general aim of BC algorithm to generate trajectory of agent by learning policy for a given state. The goal of BC for the project car parking in an action-state space can be formulated as equation (2) to generate control input υ_t using policy π given the current state x_t. The driving task for BC can be treated as a supervised learning problem [11][12][13].

The abstract of BC algorithm described in [12] requires a dataset of trajectories from the expert $\mathcal{D}$, policy representation π_θ and objective function $\mathcal{L}$. The result is an optimised policy parameters θ trained using the dataset $\mathcal{D}$ by optimising the objective function $\mathcal{L}$.

$$\mathcal{D} = \{(\upsilon_i^*, s_i^*)\}_{i=1}^{M} = d^{\pi^*} \tag{3}$$

Equation 3 describes the dataset represented by a set of control input (υ_i) and state (s_i) pair from the trajectories of the expert. The policy of the expert is used as the ground truth reward and assumed to be near the optimal policy π^* [8].

$$\ell(x^L, x^{demo}) = (x^L - x^{demo})^T (x^L - x^{demo}) \tag{4}$$

The quadratic loss function also known as ℓ_2-loss or least squares (LS) in equation (4) is commonly used as an objective function and most optimiser libraries include additional regularisation term. The x terms are vectors and loss calculates the action from agent's policy x^L against expert's action x^{demo}. Other loss functions can be used as the object function such as ℓ_1-loss, cross entropy loss, hinge loss, etc.

3.3 Evolutionary Algorithm

4 Experimental Results

Experimental result

5 Conclusions

Conclusion

References

1. E Baburaj, BR Tapas Bapu, M Tamilselvi, and Bhasker Dappuri. Smart autonomous car parking for the modern vehicles. In *Journal of Physics: Conference Series*, volume 1964, page 042070. IOP Publishing, 2021.

2. Teck Kai Chan and Cheng Siong Chin. Review of autonomous intelligent vehicles for urban driving and parking. *Electronics*, 10(9):1021, 2021.
3. Ch Q Choi. How self-driving cars might transform city parking. *IEEE Spectrum. Febrero*, 20, 2019.
4. Felipe Codevilla, Eder Santana, Antonio M López, and Adrien Gaidon. Exploring the limitations of behavior cloning for autonomous driving. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9329–9338, 2019.
5. Alejandro Correa, Guillem Boquet, Antoni Morell, and Jose Lopez Vicario. Autonomous car parking system through a cooperative vehicular positioning network. *Sensors*, 17(4):848, 2017.
6. Wael Farag and Zakaria Saleh. Behavior cloning for autonomous driving using convolutional neural networks. In *2018 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*, pages 1–7. IEEE, 2018.
7. Bosch Global. Autonomous parking in parking garages, Mar 2022.
8. Sham Kakade and Wensun. Lecture notes in cs6789 foundations of reinforcement learning, December 2020.
9. Edouard Leurent. An environment for autonomous driving decision-making. https://github.com/eleurent/highway-env, 2018.
10. Letian Lin and J Jim Zhu. Path planning for autonomous car parking. In *Dynamic Systems and Control Conference*, volume 51913, page V003T32A017. American Society of Mechanical Engineers, 2018.
11. Abdoulaye O Ly and Moulay Akhloufi. Learning to drive by imitation: An overview of deep behavior cloning methods. *IEEE Transactions on Intelligent Vehicles*, 6(2):195–209, 2020.
12. Takayuki Osa, Joni Pajarinen, Gerhard Neumann, J Andrew Bagnell, Pieter Abbeel, and Jan Peters. An algorithmic perspective on imitation learning. *arXiv preprint arXiv:1811.06711*, 2018.
13. Saumya Kumaar Saksena, B Navaneethkrishnan, Sinchana Hegde, Pragadeesh Raja, and Ravi M Vishwanath. Towards behavioural cloning for autonomous driving. In *2019 Third IEEE International Conference on Robotic Computing (IRC)*, pages 560–567. IEEE, 2019.
14. Monika Stoma, Agnieszka Dudziak, Jacek Caban, and Paweł Droździel. The future of autonomous vehicles in the opinion of automotive market users. *Energies*, 14(16):4777, 2021.
15. Rikuya Takehara and Tad Gonsalves. Autonomous car parking system using deep reinforcement learning. In *2021 2nd International Conference on Innovative and Creative Information Technology (ICITech)*, pages 85–89. IEEE, 2021.
16. Edgar Talavera, Alberto Díaz-Álvarez, José Eugenio Naranjo, and Cristina Olaverri-Monreal. Autonomous vehicles technological trends, 2021.
17. Faraz Torabi, Garrett Warnell, and Peter Stone. Behavioral cloning from observation. *arXiv preprint arXiv:1805.01954*, 2018.
18. Wenbo Wang, Y Song, Juan Zhang, and H Deng. Automatic parking of vehicles: A review of literatures. *International Journal of Automotive Technology*, 15(6):967–978, 2014.