HyperDrive: Autonomous Self Driving Car in an Urban Setting using Deep Reinforcement Learning

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Sana Haider

Syed Asad Zaman

Abstract

Ever since the Alpha go breakthrough (date here), reinforcement learning caught the attention of many researchers and developers (blah blah), and ever since then reinforcement learning has achieved remarkable results in various fields like engineering, robotics, medicine, industries. Everything is being automated and so is a car. (a bit history of SDCs) A lot of work is been done on autonomous cars (examples: Tesla, Google, etc.) but it's still an unsolved problem. (Why? give reason maybe). In this project, Hyper-Drive uses deep reinforcement learning to train a self-driving car in an urban and dynamic simulated environment. Apart from training the car, it will also do route planning to get the best optimum path. This project is conducted in the CARLA simulator offering a customizaible and realistic urban environment that is specially designed for autonomous driving research. (to be refined)

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Chapter 2

Review of Literature

This chapter provides a comprehensive literature review of the related work to blah blah

Chapter 3

Review of Literature

In the past few years, deep reinforcement learning become a very focus topic due to its success in games like Atari games, GO, and chess. Especially after the success of the project AlphaGO[6] in 2016 and AlphaZero[5] in 2017 by Google DeepMind reinforcement learning become a hot topic. Besides, a fairly recent project known as AlphaFold[2] is used to predict the protein structure has opened doors for reinforcement learning to be applied on more complex real-world problems like goal-oriented autonomous self-driving in a complex dynamic dense environment that includes route planning also. From the review of the following research papers, the authors have concluded that there is not any neural network or reinforcement architecture modeled in CARLA yet that has addressed the problem of route planning in a dynamic dense urban environment

3.1 Reinforcement Learning

When we talked about reinforcement learning it somehow works like human psychology i.e, learning from previous experiences and taking the future action based upon those experiences. In the past, RL was limited to the domain where the features are given to the RL model which was handcrafted or had a low dimensional search space. Due to this limitation, RL wasn't able to be applied to a problem where the search space was limited. For that purpose, a novel artificial agent was designed which was named as **deep**

Q-network (DQN)[4]. This agent has trained on Atari 2600 games. The only input that was provided to this agent was pixels of the game played and the score input. Surprisingly, the agent was able to achieve a professional level of success. DQN was a neural network specifically a deep neural network combined with reinforcement learning whose goal was to maximize the future reward. The limitation of DQN (mention in the paper) was that it was limited to Atari games only and didn't apply to games with higher search and state space and to 3D games.

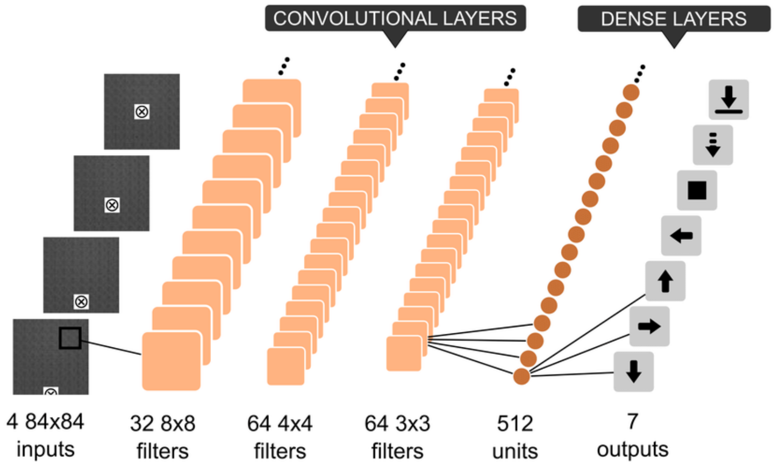

Figure 3.1: Schematic illustration of DQN

DQN was able to achieve some notable success when it comes to the games where the search space of the possible moves (b^d b is game's breadth and d is depth (game length)) was limited but when it comes to the games where the search space is pretty much large for example Chess ($b = 35, d = 80$) and especially Go ($b = 250, d = 150$) than typical reinforcement learning techniques become exhausted. Another difficulty is in the evaluation of board positions and moves. So to solve the problem of effective search space two general principles can be used:

- Depth of the search can be reduced by position evaluation truncating the tree at state s and replacing the subtree below s.
- Breadth of the search may be reduced by sampling actions from a policy p(als) that is a probability distribution over possible moves an in position

The approach used for **AlphaGo[6]** was that a deep neural network was trained on the novel combination of supervised learning from human expert games and for self-play games, reinforcement learning was used. The tree search algorithm that was used in **AlphaGo** was **Monte Carlo Tree Search (MCTS)**. AlphaGo was able to achieve the groundbreaking success of a **99.8% winning rate**. By defeating the European Champion by **5-0** and worldwide champion by **4-1**. This was the first time in the history of a full-sized game of Go that a machine was able to defeat human experts which were almost thought impossible at least for a decade. The main achievement of AlphaGo was that it has provided the solution for the games with higher search space using DQN and MCTS, which open doors for solving much more complex real world problem like autonomous self-driving in a complex environment. The limitation of this project was that AlphaGo was taking too much time while making decision which make it sometimes inefficient.

With the advancement in AI, It is now heading to a place where an A. I agent capable of learning from themselves i.e, learn from its past experiences. Just like a small kid when he/she tried to walk for the first time. At first, it stumbles a lot but a point came where it learn how to walk without stumbling. The same thing is mimicked in RL-based agents like AlphaZero. **AlphaZero[5]** is a fully generic algorithm which achieved notable success in games like **Chess**, **Go** & **Shogi**. Unlike, AlphaGo where the agent has to create a tree, evaluate board positions, and then solve the problem using the MCTS. AlphaZero, play the game just by knowing the rules of the game it doesn't require any additional domain knowledge using. And the interesting part is that it achieves this by doing self-play and reinforcement learning only. This shows that general-purpose RL can achieve a **superhuman** level performance in much more complex real-world problems.

3.2 Self-Driving Car

3.3 Path Planning

Whenever the topic of autonomous self-driving is explained we find three things in autonomous vehicle:

- perception: what it perceives from its environment
- decision-making: deciding on the perception the car made
- control system: what move or action it should take keeping in view the decision

. The problem of path planning in an autonomous vehicle is somehow dependant on these factors. Path planning in an autonomous vehicle is a hot topic in self-driving nowadays because of the complex dynamic environment, where driving a car autonomously safely to its destination is a difficult task. To solve this problem multiple solutions are provided one of them is a two-layered[1] approach. In this approach, two models are made a high-level model which produces a rough path, and a low-level model for precise navigation. Furthermore, a high-level model generates an obstacle-free path using the Improved Bi-directional Rapidly-exploring Random Tree (RRT). For the precise navigation low-level model uses the Vector Field Histogram (VFH). However, the limitation of this approach is that if we increase the number of samples then the best path cannot be expected from this algorithm.

Another approach for path planning is to use a global approach i.e, path planning that gives us a collision-free path. Ant colony algorithm (ACC) has strong adaptability and robustness unlike the traditional path planning algorithm where there is strong stability low probability bias but lack the guarantee of a path being optimal. For this purpose an optimized version of ACC is introduced, an adaptive ant colony algorithm (AACO)[3] to solve global path planning problems. The AACO algorithm optimizes the pheromone accumulation process, introduces the Manhattan distance, and introduces the adaptive factor into the search process. By this means, the search efficiency and convergence speed are improved, and a random probability selection strategy is added to prevent the algorithm from falling into a local optimum (the problem that exists when using global path planning). The limitation of this technique is that it fails in the dynamic environment and unable to work efficiently.

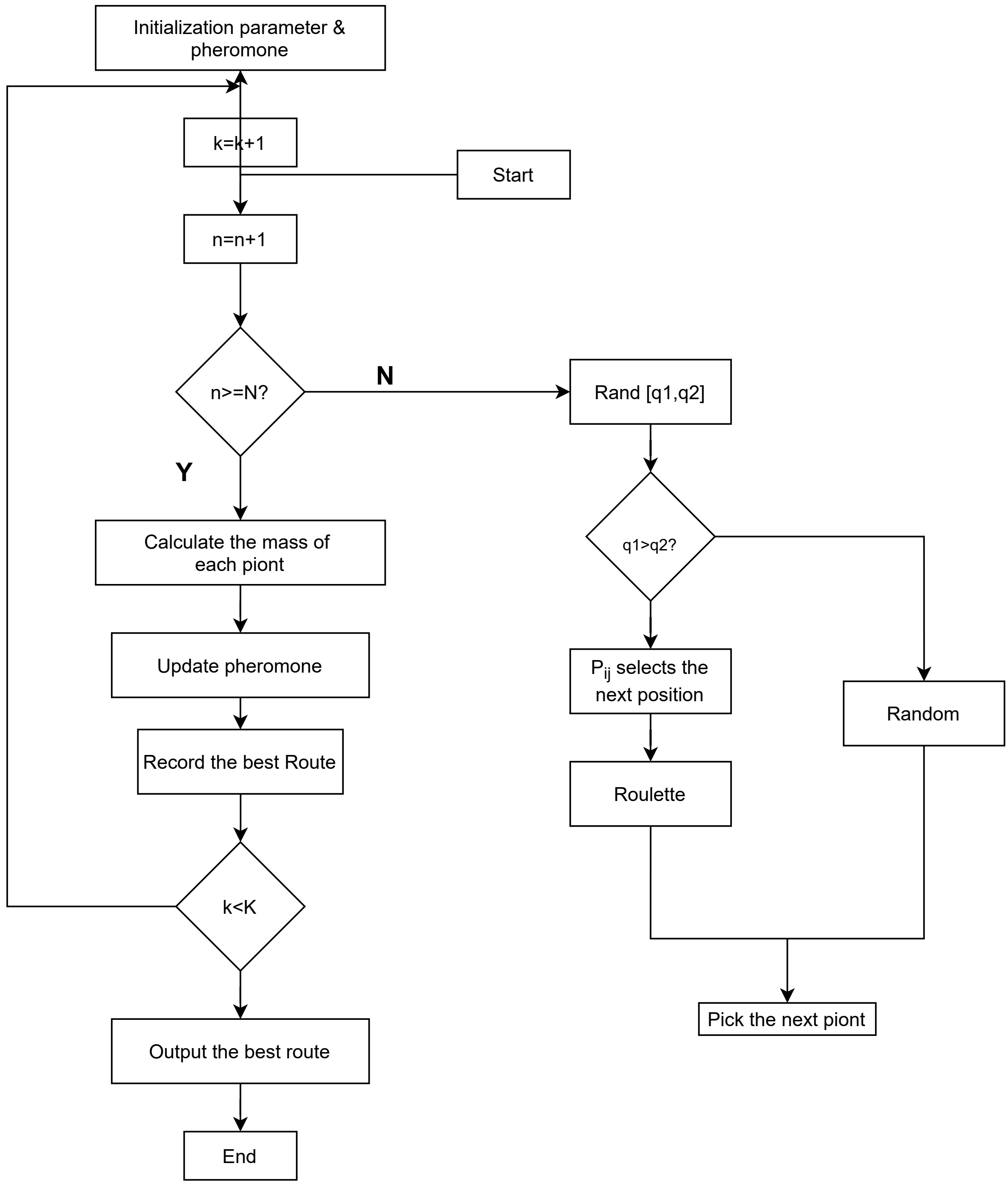

Figure 3.2: Flow chart of ACCO

Chapter 4

Conclusions and Future Work

conclusions here

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