Abstract

In the western world, health and safety is always a primary concern for car companies as they ensure that they meet all the standards and requirements to keep their passengers safe both while driving and in the event of a collision. A study in 2012 concluded that fatal road traffic incidents occur on average every 50 seconds, and road traffic injuries are sustained every 2 seconds (1). According to WHO, approximately 1.35 million people die each year as a result of road traffic collisions. As a result, this study aimed to find a way to increase traffic safety whilst maintaining or improving traffic flow and efficiency. To complete this task, numerous different techniques in the areas of Machine Learning and Artificial intelligence were considered. The most suitable option involved using Deep Reinforcement Learning to solve the given issue. Existing work showed promising results for using Deep Reinforcement Learning in Traffic control and congestion problems. Initially, this only applied to single-agent environments; however, with the introduction of Independent Deep Q Learning and more powerful computing, this allowed for multi-agent algorithms.

Therefore this thesis focused on using Deep Q Learning for the single-agent scenarios and Independent Deep Q learning for multi-agent scenarios. A single agent consisted of 1 intersection with four roads meeting at the intersection. While the multi-agent scenario consisted of 4 intersections, each with four roads meeting at the intersection. The traffic simulator used for these simulations was called SUMO. During the simulation, key metrics such as vehicle average speed, number of collisions/number of vehicles performing emergency braking and the cumulative waiting time for each episode. Deep Q Learning and Independent Deep Q learning ran through numerous different experiments, each with different parameters such as observation space and memory size. Throughout the simulations, two different actions sets were tested and analysed.

In the single-agent low traffic scenario, we saw that the more extensive action set, large observation scope and smaller memory produced the best results by decreasing collisions by 72% and increasing speed by 150%. The same trend was produced when the single-agent high traffic scenario was run.

The observation scope size and memory size were then taken and used in the multi-agent scenarios. In the multi-agent low traffic scenario with the more extensive action set out preformed both the baseline and the smaller action set by reducing collisions by 48% and increasing the average speed by 127%. However, both action sets reduced the average waiting time to 0. In high traffic demand, the same trend is repeated where the more extensive action set reduces collisions by 60% and increases average speed by 158%. From these results, it concluded that the thesis completes its objective of increasing traffic safety whilst either maintaining or improving traffic flow and efficiency.