Abstract

Autonomous vehicles are now a part of daily life. While considering hard constraints such as traffic rules and collision avoidance, an autonomous driving system should be able to maximize comfort, safety, and efficiency. The primary factor in 94 percent of all fatal crashes is human error. So, reassuringly, greater use of autonomous vehicles could limit humans' mistakes and eliminate millions of otherwise avoidable deaths. With an increase in traffic congestion, air pollution also increases. Object detection and object classification algorithms allow self-driving cars to recognize things, comprehend circumstances, and make decisions. Better ML models are needed to improve their safety and motion planning. The primary goals and objective of this project titled' Safe and efficient lane changing in Autonomous vehicles using Artificial Intelligence' is to implement Artificial Intelligence techniques to improve the safety in which Autonomous vehicles change lanes, thus reducing accidents and improving the motion planning, taking into account the different surrounding factors that affect the trajectory of Autonomous vehicles. Through the use of SUMO urban mobility software, this dissertation will implement Deep Reinforcement learning methods in a simulation environment using Q-learning methods like Deep Q Networks and Policy optimization Reinforcement Learning methods like Advantage Actor-Critic (A2C) and Proximal Policy Optimization(PPO), and the results of these methods are evaluated using different parameters. Reward parameters are defined, including comfort, safety, and efficiency. These three metrics allow us to implement a solution where an ego vehicle can make a lane-changing decision from an action space in a reinforcement learning environment in a mandatory lane-changing scenario. After evaluating the learning performance of different RL methods mentioned above, it was deduced that Policy Optimization-based Reinforcement Learning models tend to perform better than Q learning methods. Policy-based RL methods tend to learn the value of the policy by steps of exploration in the Reinforcement Learning environment. In contrast, Q learning methods learn independent of the agent's action in the environment. New Q learning methods like Double DQN and DQN can improve their performance compared to DQN being used without any add-ons. The results and findings and the implementation of the approach are further discussed in the report.