Introduction

The authors present Nav-Q, a quantum-supported DRL algorithm for collision-free navigation of self-driving cars1. Nav-Q leverages quantum computation for improving the training performance without the requirement for onboard quantum hardware.

Related Works: The authors review the existing literature on DRL methods for CFN and QRL methods for various tasks. They identify the gap between the current QRL approaches and the CFN problem and propose a novel hybrid quantum-classical architecture to bridge it.

Problem Formulation: The authors model the CFN problem as a POMDP, and define the car and pedestrian models, the state, action, observation, and reward spaces, and the transition and observation probabilities. They also describe NavA2C, a classical DRL-based architecture that serves as a baseline for comparison with Nav-Q.

**How does Nav-Q work?**

Nav-Q is a quantum-supported Deep Reinforcement Learning (DRL) algorithm designed for collision-free navigation (CFN) of self-driving cars1. Here’s a high-level overview of how it works:

Quantum Reinforcement Learning: Nav-Q leverages quantum computation to improve the training performance of the DRL algorithm1. Quantum reinforcement learning has demonstrated faster convergence and improved stability in simple, non-real world environments1.

Actor-Critic Approach: Nav-Q is based on the actor-critic approach, where the critic is implemented using a hybrid quantum-classical algorithm suitable for near-term quantum devices1.

Performance Evaluation: The performance of Nav-Q is assessed using the CARLA driving simulator, a standard benchmark for evaluating state-of-the-art DRL methods1. Empirical evaluations show that Nav-Q surpasses its classical counterpart in terms of training stability and, in certain instances, with respect to the convergence rate1.

Quantum Noise: The performance of Nav-Q is also evaluated using noisy quantum simulation. The quantum noise deteriorates the training performances but enhances the exploratory tendencies of the agent during training1.

Please note that this is a high-level summary. For a detailed understanding, you may want to read the full paper