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# Adaptive Path Planning in Stochastic Environments Using Deep Q-Learning

Abstract:

The problem of path planning in stochastic environments represents a significant challenge for autonomous robots due to unpredictable changes in the environment that can render preplanned paths sub-optimally. This project will develop a simulation based framework by using Deep Q-Learning to enable a robotic agent to adaptively plan paths in real-time accounting for the stochastic nature of its operating environment. Unlike traditional path planning algorithms that assume a static world my approach will dynamically adjust to environmental changes such as moving obstacles or variable terrain conditions.

This work is original as it extends the Deep Q-Learning algorithm to specifically address the unpredictability inherent in real-world scenario, a facet that is often simplified or overlooked in robotic simulations. The originality also lies in the application of a reinforcement learning algorithm that continuously learns and improves from the stochastic transitions of the environment rather than relying on pre-computed models.

The evaluation of the work will be conducted by comparing the performance of the robotic agent in various simulated stochastic environments against traditional path planning algorithms. Success will be measured by the agent's ability to reach its goal efficiently without prior knowledge of the environment's dynamics, its adaptability to sudden changes, and the computational resources required for real-time decision-making.

Literature Review:

Robotic path planning has evolved significantly with the advent of stochastic modeling which is more accurately reflected in the unpredictable nature of real-world environments (LaValle, 2006). The application of Deep Q-Learning to this field is an increasing area of research, promising to enhance the adaptability of autonomous systems (Mnih et al., 2015).

The work presented at the IEEE International Conference on Robotics and Automation (ICRA) by Karaman and Frazzoli (2010) introduced the RRT* algorithm offering a near optimal solution to path planning. Though RRT* is influential, its deterministic nature limits its application in environments where uncertainty is a key factor. This limitation underscores the need for adaptive algorithms that can operate under uncertainty a gap that Deep Q-Learning can potentially fill.

At the IEEE International Conference on Intelligent Robots and Systems (IROS), Silver et al. (2010) demonstrated the use of Monte Carlo Tree Search (MCTS) in robotics a method that handles uncertainty by simulating potential future states. However, the MCTS does not inherently learn from interactions with the environment a feature that Deep Q-Learning can integrate as shown by Mnih et al. (2015) in their groundbreaking work published in Nature.

The International Journal of Robotics Research has featured work by Thrun et al. (2005) on probabilistic robotics provides a comprehensive framework in dealing with uncertainty. While the work is foundational it does not leverage the recent advances in deep learning that enable end-to-end learning from high-dimensional sensory inputs which is the most important point of issue of Deep Q-Learning.

Osband et al. (2016), in their presentation at Advances in Neural Information Processing Systems (NIPS), introduced bootstrapped DQN which incorporates uncertainty into the learning process. This approach is relevant as it aligns with the stochastic nature of the environments considered in this project. However, the application of bootstrapped DQN to the specific challenges of robotic path planning in highly stochastic environments remains as an open question which this project aims to address.

The proposed project builds upon these foundational works by integrating the robustness of probabilistic planning with the learning capabilities of Deep Q-Learning. This project's idea and its originality lies in the development of an adaptive path planning algorithm that learns to navigate stochastic environments.

Duckworth and Cohn's (2017) insightful investigation into the realm of predictive state representations (PSRs) has given promising role of PSRs in distilling the complexities of dynamic environments into a format that is amenable to learning. Such advancements can prove invaluable to the evolution of adaptive path planning algorithms particularly when infused with the capabilities of Deep Q-Learning methodologies.

The foundational principles of reinforcement learning, as outlined by Sutton and Barto (2018), provide a comprehensive backdrop for modern approaches in adaptive path planning. Their innovative work delineates the core algorithms that underpin the field offering a clear framework for understanding how agents can learn to make decisions in complex environments. The integration of these principles with Deep Q-Learning as proposed in this project represents a natural progression in the quest to develop autonomous agents capable of navigating stochastic environments with a high degree of adaptability.

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