Applying FastMDP to complex aerospace-related problems

Markov Decision Processes (MDPs) are a powerful technique for modelling sequential decision-making problems which have been used over many decades to solve problems in robotics, finance, and aerospace domains. However, MDPs are also known to be difficult to solve due to explosion in the size of the state space which makes finding their solution intractable for many practical problems. This dissertation describes an algorithm known as FastMDP which solves a certain subclass of MDPs very quickly (typically dozens to hundreds of milliseconds) on desktop and embedded processors. Several applications of the algorithm are provided to demonstrate its utility: (1) air-taxis or package delivery drones navigating to vertiports avoiding collisions with each other and mountainous terrain, (2) terminal airspace management of multiple air-taxis using concentric rings which circulate traffic while awaiting landing, (3) pre-departure flight planning of 2000+ aircraft, (4) general aircraft 1-versus-many collision avoidance, and (5) unmanned aerial vehicle navigating between and around buildings (e.g., skyscrapers) in New York City. Parallelism inherent in the algorithm is examined and a Graphics Processor Unit (GPU) based implementation is described demonstrating the scalability of the algorithm either for simulating many (2000+) aircraft simultaneously or

for efficiently making decisions when considering high-fidelity aircraft dynamics. FastMDP is compared to other popular algorithms such as Optimal Reciprocal Collision Avoidance (ORCA), Monte Carlo Tree Search (MCTS), and Rapidly-exploring Random Trees (RRT and RRT\*) to examine tradeoffs between the different algorithms, studying both collision avoidance performance and computational performance. A taxonomy of MDP subclasses is defined, proofs are provided for a narrow subclass of MDPs, and analysis is provided showing how the FastMDP algorithm might be applied to a larger subclass of MDPs in the future. This dissertation closes by providing a roadmap for future researchers to follow to expand on the FastMDP approach which could potentially lead to a revolutionary approach to solving Reinforcement Learning problems resulting in improved explainability properties, transfer learning, and data-efficiency properties