Effectiveness of Search-Based Testing on a Deep Reinforcement-Learned Swarm Controller

Bachelor's Thesis

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Context

The popularity of unmanned aerial vehicles (UAVs), also known as "drones," has laid the groundwork for interest in cooperating UAVs. In particular, those groups of UAVs that are referred to as *swarms* are the subject of many research efforts [1]. Especially of interest to us are *decentralized* or *distributed* swarms, where the individual UAVs are autonomous in their decision-making rather than being controlled by a single centralized entity [2]. One approach to implement a controller for this type of system is to use deep reinforcement learning (RL). Compared to classical methods of implementing drone controllers, a deep RL approach may produce a controller that does not require precise models or measurements of drone dynamics and can be scaled with swarm size [3].

To challenge the behavior of autonomous systems, existing approaches utilize scenario-based testing (SBT) combined with metaheuristic search methods to test UAVs that operate individually [4]. This approach is based on established methods that have been utilized in the autonomous car domain to build relevant scenarios and search for scenario configurations that elicit "edge case" unsafe behaviors of the system under test (SUT) [5]–[8]. Specific to deep RL controllers, the authors of [9] have utilized a similar approach to search for "faulty episodes." However, to the best of our knowledge, there is currently no existing work that tests the behavior of a deep reinforcement-learned decentralized drone swarm. Additionally, deep RL systems can be more brittle than classical controllers, so it is not clear if metaheuristic search methods will perform well.

Goal

The goal of this thesis is to determine the effectiveness of search-based testing to challenge the behavior of a deep reinforcement-learned swarm controller operating in an environment with obstacles. We propose using the system of cooperating UAVs developed in [3], which is designed to travel from a starting location to a goal location while maintaing a predefined proximity between UAVs and avoiding collisions. Metrics to evaluate the global task of the system (i.e., travel to the goal) and quality attributes (i.e., speed, formation spread, safety) should be specified as a fitness function. Then, at least two approaches to search for test cases by varying obstacle characteristics should be evaluated against each other: random search and at least one metaheuristic search. As an optional extension to this work, search-based testing can be combined with metamorphic testing to utilize a metamorphic test oracle, such as in [10].

Working Plan

1. Build familiarity with existing scenario-based testing and search-based testing approaches.
2. Build familiarity with properties of a decentralized drone swarm and of the SUT [3].
3. Implement a fitness function for search-based testing; this will be used to determine the fitness of individual test cases that are found.
4. Design a scenario by describing the functional scenario and logical scenario properties [5].
5. Implement random testing and search-based testing of the SUT; if useful, the STARLA tool developed in [9] can be used.
6. Evaluate the performance of the different approaches using metrics for comparison.
7. Write the report and presentation.

Deliverables

- Source code of implementation using MIT License incl. documentation.
- Final thesis report written in English and in conformance with TUM guidelines, comprehensively describing the methodologies, implementation, and findings.
- Presentation of the work at the Chair.

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