Research proposal for student research project 2018

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# Problem Setting

Our goal is to train a team of autonomous drones to explore an unknown area as efficiently as possible in order to find a given target. This setting leads to a wide range of problems. We want to focus on the following aspects, whereby the order represents our priority.

1. Synchronisation

Every drone in the team must synchronize with other drones to avoid work that has already been done. This implies that the drone’s individual decision-making, i.e. path planning depends not only on its own past decisions and its current environment, but also on decisions made by other drones. The decision-making may be done by a central control drone or by all drones simultaneously. This setting further implies that the connection to other drones may get lost if the drones travel too far from each other.

1. SLAM

Every drone must explore its surrounding area in order to find the target. This is known as Simultaneous Localisation and Mapping (SLAM). This can be done using any available sensor input, e.g. camera frames and GPS.

1. Object Recognition

The team of drones should be able to identify any given target and communicate this event back to the operator.

Assumptions

* Search area is limited beforehand by the operator
* Target is easy to identify
* Exploration is time-critical
* Drones are able to fly stable in the given direction and are already able to avoid small obstacles (trees, power poles, etc.) by themselves.

Out of scope:

* Technical details about drone hardware and communication
* Optimization with regard to most efficient use of hardware resources

# State of the art

Existing approaches:

* Reinforcement Learning (RL) for a single drone, search and rescue
* Methods to achieve shortest path (RL)
* Mostly tested in simulation, not implemented in real-time

We have to incorporate both Deep Learning and Reinforcement Learning

* Delay between action and rewards
* Deep Learning (DL) assumes independent actions, while in RL states are highly correlated
* Effectiveness is dependent on the exploration strategy used
* Frontier exploration
* How well does it resemble the real-world scenario

To do

* Learn collision avoidance
* exploration
* victim discovery and identification

# Data Foundation

Our ultimate aim is to use a team of autonomous drones for Search and Rescue missions via simulations. Hence the requirement for real time data is not mandatory.

The simulator uses plugin that can you can drop into any existing, or new, unreal environment. It can generate training data through images for each frame.

A more complex way to generate training data is through Application programming interfaces (API). These APIs collect sensor and ground truth data from the drones, as well as various images. With their help, the code used to test drones in the simulator can be transferred to an offboard computer and used on real drones

The following are simulation platforms which will be evaluated in due course for its complexity, performance, financial cost and hardware requirements:

* **SITL** (Software In The Loop) most commonly used by developers.
* **Gazebo**. is the official DARPA virtual robotics simulator
* **XPlane-10**: a commercial flight simulator with a rich 3D interface
* **RealFlight**: a commercial flight simulator with a rich 3D interface and ability to design custom vehicles
* **AirSim**: platform for artificial intelligence (AI) research to experiment with deep learning, computer vision and reinforcement learning algorithms for autonomous vehicles.

# Research Idea

The experiment will focus on developing a novel reward function. Using a combination or subset of the following parameters will be tested to evaluate performance and provide an optimal solution.

* distance to other drones - sufficiently far such that coverage is not doubled but to also ensure that coverage is not missed. It will be weighted to be more lenient on allowing double coverage.
* exploration feedback - maximize coverage as quickly as possible
* hard or soft coverage techniques - drones coverage is gradient - more confident nearby and less confident far away
* maximum number of nearby drones - penalizes drones that cluster together.
* different tiers of drones with different reward functions - one tier focuses on maximization of distance covered whereas the other focuses on filling in gaps left by first tier.

This will be compared to current State of Art techniques.

# Tangible outcomes

We will be making use of the open source software for our project and provide results via software documentation (story about requirements, design, implementation). In addition to this, we will also be including a demo or a tutorial in the form a video representation. The video will depict the simulation of the drone navigating through a known/unknown path in search of a particular object/person, while avoiding obstacles on the way. The data regarding the location and optimal path will be transmitted to the central hub after which the rescue mission can take place.

# Work Plan

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| Preparation | April - May | analyze simulator systems and perform background research |
| Evaluate and  Implementation | April - June | Implement experiment design and State of Art to current baseline |
| Testing | May-Oct | experiments, adjust algorithms, re-evaluate experiment |
| Finalization | Presentation 1: May-June  Presentation 2: Sep-Oct  Final Presentation and Documentation: Oct-Dec | Prepare presentations, report, and software documentation |

# Team

Our team consists of

* Benjamin Hogstad (277456)

Received a Bachelors of Science in Mathematics with a Chemistry minor from the University of Oregon. Prior experience in a regulated chemical laboratory as quality assurance and project manager. United States of America

* Ramya Raghuraman (277488)

Received a bachelor degree in Electronics and Communication. Experience in Accenture as an associate software developer. India.

* Krithika Murugesan (277537)

Prior experience in Web and Click Stream Analytics for Search Engine Ad monetization and Optimization. India.

* Mohana Nyamanahalli Venkatesha
* Michael Ruchte (277530)

Received a bachelor degree in Political Science and Economics. Experience in Computer Vision, working experience in software development. Germany.

# References

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Challita et al (2018): Deep Reinforcement Learning for Interference-Aware Path Planning of Cellular-Connected UAVs