MIT Think Project Proposal

Deployment of a Collectively Optimized Swarm of Autonomous Micro UAVs for Accurate 3D Reconstruction of Destroyed Buildings During Disaster Recovery

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ABSTRACT

Natural disasters inflict devastating loss of life. Further magnifying this impact is the roughly tenfold increase in the global rate of recorded disasters, from 39 in 1960 to 396 in 2019, cementing the importance of improving post natural-disaster response. Although initial research has investigated the use of drone swarms to locate survivors in disaster environments, these approaches do not address the specific complications that arise when drones (referred to here as "control" drones) locate destroyed buildings that may have survivors. In that case, drones would have to enter the building to identify them. This project aims to improve upon this distinct type of post-disaster response while following the aforementioned swarm-based solution by providing an internal 3D mapping of buildings possibly confining survivors.This allows rescuers to navigate through damaged buildings with more precision and awareness while conserving their rescue effort to only confirmed locations of survivors. In this solution, the larger control drones carry micro-drones with them and would serve as a control station for this swarm of less computationally powerful CrazyFlie micro-drones upon arriving at a selected building. These micro-drones would have the ability to fit through tighter spaces facilitating a more thorough mapping of targeted buildings. Upon deployment by the control drone, the swarm of micro-drones would navigate in a decentralized manner according to the gradient-based path planning algorithm. Using RGB-D sensors, the drones would take images and poses for

subsequent forwarding to the control drone to form a 3D reconstruction of the post-disaster environment, utilizing LSD-SLAM.

IDEA

Natural disasters are capable of annihilating buildings, leaving nothing but rubble in their wake. This capability is what makes disasters so dangerous, as human lives are at the mercy of the buildings in which they reside. The issue is even more relevant now as the rate of natural disasters has increased tenfold over the past 60 years (from 39 to 396) (Vision of Humanity, 2021). This is not only alarming because of the already devastating effects that these disasters have on communities and people, but also because of the fact that as cities grow more dense, the effects of these disasters become more pronounced. While no group of individuals is able to control the rate of natural disasters, it is possible to control the response to them. It is practically impossible to rescue survivors without knowing their location. Thus, it follows that the ability to rapidly locate survivors would drastically reduce the number of deaths and injuries of those caught in the aftermath (Chiu et al., 2020). One of the latest developments in locating survivors faster while expending fewer resources has been the use of Autonomous Drone Swarms. This stems from swarm intelligence, a subfield of artificial intelligence that takes advantage of the emergent properties of setting specific behaviors to individual nodes of a swarm. There are several advantages of using swarms as opposed to a singular, more complex robot. Firstly, if a singular robot were to fail, it would be more difficult and expensive to replace than cheaper robots (Dorigo et al., 2014). This difference is crucial in complex situations like natural disasters. Additionally, swarms are able to accomplish tasks at speeds that would be impossible for a singular robot to accomplish. By definition, drone swarms are more scalable while also possessing the benefit of being able to accomplish multiple tasks simultaneously. Due to the scalability of swarms, they are a very versatile tool in these natural disasters where the environment can differ in many ways (Meshcheryakov et al., 2019).

Modern approaches implement the use of search parties, often consisting of a large number of people and vehicles. These parties are unable to cover larger areas quickly and the large vehicles often result in heavy financial costs. Autonomous Drone Swarms solve both of these problems as not only are drones much cheaper and more expendable but, large swarms of drones can cover areas at much faster rates. In simulation, swarms were consistently able to locate 90% of survivors in a post-disaster environment (Arnold et al., 2018). These results are a great proof of concept for the use of drone swarms in Search and Rescue. However, the act of locating a survivor within a ravaged building and the insight that drones, specifically smaller quadcopters, give has not been addressed here and in much other research. To solve this, we propose a novel idea: larger drones within the search and rescue swarm would carry a swarm of microdrones. Upon the discovery of a building with survivors, the swarm of microdrones would be released. The microdrones would move in a decentralized manner, mapping out the environment collectively which would allow rescuers to have a precise understanding of the buildings they will enter. Search and rescue is best tackled through a decentralized approach. Centralized approaches tend to be more efficient and more thorough in their coverage of an area, but in an environment where communication is scarce, a decentralized approach must be used. (Jamshidpey et al., 2021).

Intuitively, smaller microdrones would be more ideal for navigating through a highly damaged building (McGuire et al., 2019). The CrazyFlie drones measure in at 27 g with its dimensions being 92 mm x 92 mm x 29 mm and with many larger drones used in post-disaster SAR having payloads of over 1000 g while also being wide and long enough to carry at least four CrazyFlie drones on top, the idea is certainly viable. CrazyFlie drones were chosen because their robust and open source nature allows for easy modification and addition of algorithms directly to the drones. Building custom drones for this application may prove to be too difficult within the time constraints and would most likely be of lesser quality than the CrazyFlie drones. Furthermore, CrazyFlie drones have been proven to be applicable to and effective at similar tasks in other research (Park & Kim, 2021). CrazyFlie drones can interact with each other through the CrazySwarm platform (Preiss et al., 2017). CrazySwarm is entirely open-source and the CrazySwarm simulation platform uses the BITCRAZE API.

Until recent years, microdrones have been limited by their computational power. Despite these limitations, decentralized swarms have been successfully implemented with the use of gradient based planning to not only avoid collisions with each other, but also to avoid collisions with static and dynamic objects in the environment (Zhou et al., 2021). Simultaneous Localization and Mapping (SLAM), although not able to run on the micro-drones due to processing power, is made possible through the use of the control drone. In 2020, a study demonstrated the use of LSD-SLAM as a way to utilize more conventional mapping methods as opposed to gradient based methods. Each drone in the study was equipped with an inexpensive, lightweight RGB camera and individual drones were able to form point clouds within a Gazebo simulation (Messina et al., 2020). Although ORB-SLAM is more accurate, LSD-SLAM is more effective at 3D reconstruction because it uses a feature-less algorithm unlike ORB-SLAM, which allows it to extract more data and more data points from each picture (Wang & Shahbazi, 2019). Furthermore, the mapping algorithm of LSD-SLAM would only be possible alongside the localization of the swarm. Each node of the swarm has odometric sensors, these sensors give data that allows for localization. This combined with the data from the RGB-D cameras is sent to the control drone to complete the SLAM process. Internet of Things approaches have already been able to successfully maintain a network of sensors, showing how sensor fusion from a decentralized swarm of drones is already possible with a base control station, proving how SLAM can be implemented in the swarm with the presence of a larger drone (Sadrollah et al., 2014).

One of the issues facing autonomous drone swarms has been the path planning of swarms. What separates this idea from much of the current work in the field is the aim to use a decentralized swarm as opposed to one with centralized path planning (Madridano et al., 2020). Gradient based path planning will be used which has been shown to be computationally light enough for small drones to successfully navigate through an unknown environment (Zhou et al., 2021). Since the goal of the proposed system is to map out a building, a coverage path planning algorithm is needed. We intend to implement Swarm Gradient Bug Algorithm (SGBA), a coverage path planning algorithm that has been implemented with CrazyFlie drones. Bug algorithms would normally fail at solving an unknown environment without GPS but SGBA was designed for this task (McGuire et al., 2019). Drones following SGBA perform “wall following,” as if it were solving a maze.

Plan

We will develop a decentralized swarm system consisting of 3 micro-drones and a model control drone. This swarm will be released into an environment simulating a destroyed building to reconstruct a 3D map of the building’s interior. We will simultaneously work on the swarm controller and the multi-robot SLAM.

We will start by implementing SGBA into a simulated swarm in the CrazySwarm simulation platform. SGBA is freely available on Github (Mcguire, 2019). Since CrazySwarm operates with the high level interface, pycrazyswarm, a python script will be created using the code provided on Github. This algorithm will be tested in the ROS Kinetic simulation environment, ARGoS. ARGoS is optimized for multirobot simulations and it generates random environments procedurally. The ROS environment will be connected to the implemented SGBA controller and the CrazySwarm simulator (McGuire et al., 2019). The swarm of three CrazyFlie drones will be released from a starting position in 100 randomly generated environments in simulation. Coverage statistics will be provided by CrazySwarm interface. We aim to achieve 75% coverage of the environment on average and a 70% return rate. Upon reaching that threshold, we will incorporate our algorithm into a physical swarm. To accomplish this, we will first have to add three attachments to the CrazyFlie 2.0 drone made available through Bitcraze: a “Multi-ranger deck”, a “Flow-deck”, and a “CrazyRadio PA”. The Multi-ranger deck allows the drone to detect objects near it and is enhanced when paired with a Flow-deck. The Flow-deck allows the drone to perform basic visual odometry providing a gateway for our SLAM technology. The CrazyRadio PA is a 2.4-Ghz wifi band that will allow the micro-drones to communicate with each other and send the control drone their poses. Once the battery has depleted to 50%, the system will coordinate an inbound mission. We will run 15 preliminary swarm tests in an enclosed area in Upper Dublin High School and once an average coverage of 70% is achieved, we will begin incorporating our multi-robot LSD-SLAM algorithm onto our physical swarm.

We will be working on LSD-SLAM in parallel to the swarm path planner. In LSD slam’s current state, it does not support multi-robot systems. However, this task should be feasible, and has been proven to be possible with other SLAM algorithms. First, we will set up LSD-SLAM with one node using a camera connected to a computer with ROS. The camera will use Direct

Sparse Odometry (DSO), a form of visual odometry that enables creation of a pose map with the camera alone (Boyd, 2017). LSD-SLAM's source is on Github (Engel, 2014). Once we have successfully implemented LSD-SLAM with one camera, we will begin to adapt the base LSD-SLAM to make it Multi-Robot compatible. Using an established multi-robot SLAM framework (Forster et al., 2013), we will start with a Collaborative Structure from Motion (CSfM) system which will create pose maps for each computer camera. When two maps are recognized as overlapping, they will be merged and the computer's camera data will be focused into the merged map. With the system already being on ROS, it should be relatively easy to transfer to a drone system by replacing the camera's output with the drones' camera outputs.

We will then assemble our model control drone. Since we do not intend for the control drone to fly and we are just using it as a proof of concept, we will 3D print a model drone. We will attach a Jetson Nano with a CrazyRadio PA to the 3D printed drone. The Jetson Nano will serve as the onboard computer for the model control drone and it will be responsible for creating the map. At this point, all the components of the system will have been created and we will be able to test our whole system in a physical environment. First, we intend to use an enclosed area inside Upper Dublin High School to make sure our system works as intended. Once the mapping has achieved reasonably accurate form (from observation), we will then test the system in a research laboratory that we have gained access to through our mentor. We will test our system 15 times inside the laboratory, obtaining the average coverage, return rate of the drones and maps.

We will evaluate the performance of our swarm mapping system by qualitatively observing the completeness and accuracy of the point cloud. Quantitatively it would be best to use a laser scanner for an accurate 3D model of a test environment. That would allow us to evaluate the standard deviation of the point cloud in comparison to a 3D model of the test environment using an algorithm like nearest neighbors (Wang & Shahbazi, 2019). This could be possibly provided by the MIT THINK Team. If that is not possible, we will use fine-tuned devices to measure distances between walls and other obstacles to determine the map's accuracy based on the ratios between measurements. The SGBA Algorithm will also be evaluated on how many rooms it enters and how many survivors are captured on the micro-drones cameras.

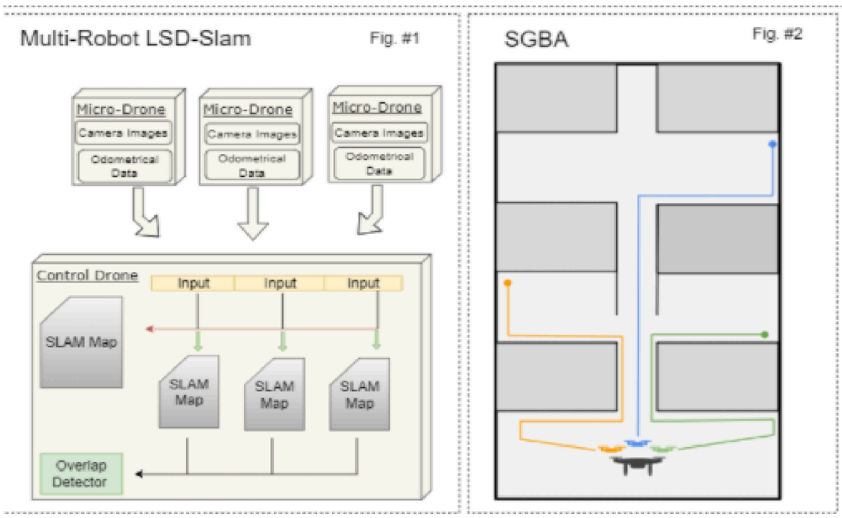

Fig. 1 Multi Robot LSD-SLAM
When the overlap detector detects an overlap in two of the SLAM maps, it will merge the maps into one and further data will be sent directly to the merged map.
Fig. 2 SGBA
The wall following mechanism is shown. The swarm still places importance on coverage so the blue drone travels in its predetermined preferred direction while the other two travel left and right respectively.

The MIT Think Funding will be used to purchase the following: three CrazyFlie 2.0 drones, three flow-decks, three multi-ranger decks, and four CrazyRadio PA systems.. The three CrazyFlie drones will be purchased on the BitCraze website and we have already acquired the Jetson Nano from previous work.. The addition of the top-notch resources of the MIT Think Team would elevate our project to the highest level in three critical ways. First, the insightful mentorship would add significant depth to our nuanced understanding of relevant algorithms and mathematics. Second, the experience-based advice on the engineering process would grant the exposure we need, essential to creating a working prototype. Finally, we're certain that there are inevitable intangible benefits that would arise from interacting with the MIT Think Team that would not only significantly enhance our project in the short-term but also ourselves long into the future.

Item	Cost per Item	Amount	Total ($955.12)	Link
CrazyFlie 2.0	$180	x3	$540	crazyFlie 2.0
Multi Ranger	$69	x3	$207	Multi Ranger Deck
Crazy Radio PA	$25.88	x4	$103.52	Crazy Radio PA
Flow Deck	$35	x3	$105	Flow Deck

As of now, we have the CrazySwarm simulator and ROS installed. We would like to continue the project in the form of the following milestones with deliverables on these deadlines:

1. **3/1/21 Fully implement SGBA swarm in simulation**
2. **4/15/21 Implement SGBA on physical swarm**
3. **4/15/21 Complete software for multi-robot LSD-SLAM**
4. **4/29/21 Build model control drone and connect swarm to control drone**
5. **5/28/21 Successfully use swarm to map out a physical environment**
6. **6/12/21 Fine tuned pipeline, possibly in multiple environments**

We anticipate running into challenges during the implementation and testing of our swarm system. We do not expect our swarm to transfer seamlessly from simulation to our field environment, especially given an unknown cluttered environment. This can be solved through fine tuning of the algorithms based on our real world testing. We also expect there to be communication challenges between the micro-drones themselves, and the model control drone. If the built in 2.4GHz ISM band radio from the micro-drones is not sufficient, we can switch to a UWB(Ultra Wide Band) solution. This would significantly increase the communication accuracy between nodes while simultaneously reducing interference. Furthermore, we expect that unknown cluttered environments might challenge the collision avoidance system of SGBA controlled swarms. Although SGBA is capable of collision avoidance, it may be useful to take inspiration from trajectory planning algorithms such as EGO-SWARM that perform very well at high speeds in cluttered environments. EGO-SWARM treats its path planning as an optimization problem, taking into account collisions and feasibility of movement.

Although both of us intend to understand all aspects of the project, it will still be necessary to allocate tasks to maximize our efficiency. Nicholas will primarily be responsible for the SLAM algorithm and Thomas will primarily be responsible for the planning of the swarm. It will be necessary for both of us to understand the processes behind each system as we will have to combine them eventually. We facilitate communication through Discord and Messages. We also communicate at school as we both attend Upper Dublin High School. We will document our progress in physical research notebooks, online documents, and Trello. Trello is a project organization software that will allow us to share checklists and any research notes.

Personal Interest

The field of artificial intelligence has always had a pull on us. The fact that artificial intelligence, the future, stems from simple math concepts has always made the frontier feel tangible. We thoroughly enjoy how there are so many separate tools, each with their own advantages, and learning about them feels like obtaining a new piece to a grand puzzle in the sense that each algorithm can solve problems in ways that other algorithms could not. Over the past couple of years, we developed an interest in drones, specifically the software aspect of them. Their versatility and relative simplicity gave us an outlet to learn about artificial intelligence beyond the confines of a computer. When we found out that there was a new, separate field of research designed to capitalize on their capabilities while simultaneously mitigating their weaknesses, we couldn't have been more excited. The recent aftermath of a tornado caused by Hurricane Ida led us to the natural disaster aspect of our project. The twreaked havoc on our highschool and its surrounding area, devastating the homes of many of our friends. Until then, we have never been so up and close to a hurricane of that magnitude and as a result, we wanted to see what mark that we could make on that issue. In addition to the research we have doneon swarm intelligence and SLAM, we have worked on many artificial intelligence related drone projects. We have successfully implemented PSO swarm algorithms in simulation for local minimum detection. For this project, we will need to become more familiar with multivariable calculus and linear algebra, specifically partial derivatives, linear transformations, and Jacobian matrices and determinants.

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