

Autonomous Aerial Mapping and its Applications for Emergency Response

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Abstract—Navigating unknown structures (e.g., buildings or caves) can be a dangerous and challenging task for emergency responders. This risk can be reduced by capturing detailed 3D maps of unseen environments with a robotic sensor platform and using them to assess and visualise the unknown structures. Many existing approaches require offline processing or human oversight to produce high-fidelity maps, which precludes their use in real-time scenarios with limited communication. This paper investigates the use of an autonomous aerial mapping solution that could capture detailed 3D maps of unknown structures in real-time without requiring human intervention.

I. INTRODUCTION

Determining how emergency responders can safely move around structures is a time-critical and life-preserving task in disaster scenarios. These structures can be man-made (e.g., buildings) or natural (e.g., caves). Some structures may have known layouts but even these can be difficult to navigate if they are partially collapsed and their structural integrity is compromised. Unknown structures present a particular challenge as they require exploration to find open spaces (e.g., where survivors may be present) in addition to identifying safe paths for responders. Exploring these structures is often a dangerous task that needs to be performed rapidly while also ensuring the safety of the emergency responders.

Robotic sensor platforms can mitigate the risk to responders by exploring and mapping structures before they enter. The 3D maps captured by a robot can be used to assess the integrity of a structure and identify safe paths around it for the responders to follow. Many types of robot platform can be used (e.g., wheeled, legged or aerial) to capture these maps but this paper focuses on aerial platforms as they can often traverse the most challenging environments (Fig. 1).

Autonomously mapping structures with an aerial robotic platform requires four key components: (i) measurements of the environment are captured by a 3D sensor (e.g., a depth camera or LiDAR), (ii) a localisation system determines the sensor positions from which measurements are captured so they can be combined into a 3D map, (iii) a view planning approach decides where the robot should capture measurements from next in order to improve the map and (iv) a path planning algorithm determines how the robot can move from its current position to the chosen view without colliding with obstacles in the environment.

Existing approaches to the mapping problem can typically either obtain detailed maps with human intervention or capture lower resolution maps autonomously. Approaches



Fig. 1. Photograph of a DJI M600 drone capturing a 3D map of a building.

that can obtain high-fidelity maps usually need to capture a human-directed initial survey of the environment. This coarse map is processed offline and used to propose views that can refine the map by capturing additional measurements. Some approaches can perform mapping autonomously but these typically need to impose simplifying assumptions on the captured measurements, which limits the map fidelity.

This paper investigates the use of an autonomous aerial mapping system for emergency response. Measurements are captured by a LiDAR attached to the underside of a hexrotor drone. The sensor position is localised with VILENS [1], a visual-inertial-lidar odometry system. Views to improve the map are planned by the Surface Edge Explorer (SEE) [2, 3], a measurement-direct view planning approach. Collision-free paths between views are planned using the Adaptively Informed Trees (AIT*) algorithm [4, 5]. This mapping system would be capable of obtaining high-fidelity maps of unknown structures in real-time without requiring human intervention.

The remainder of this paper is structured as follows. Section II presents an overview of related mapping literature. Section III investigates an autonomous aerial mapping system. Section IV presents simulation results of SEE mapping buildings with an aerial platform. Section V presents results from real-world experiments performed with an early prototype of the mapping system and discusses the motivation for future work. Section VI reviews the mapping system capabilities and its emergency response applications.

II. RELATED WORK

The core component of an autonomous mapping system is the view planning approach. This determines where sensor measurements are captured when building a map of the

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environment. Some view planning approaches are capable of proposing and selecting views without any existing structural information, allowing their mapping systems to operate autonomously, but many require an initial survey to be performed by a human operator. These approaches [6–9] represent the map as a surface mesh of connected sensor measurements. The initial human-directed survey produces a coarse surface mesh, which is processed by the view planning approach to propose new views that can refine the mesh by capturing additional measurements. These measurements are processed offline to refine the map. This allows the approaches to obtain detailed maps but means they are unable to operate autonomously or provide real-time information.

Some view planning approaches [10–14] are able to perform autonomous mapping in real-time by using a volumetric map representation. This simplifies the view planning problem by aggregating sensor measurements into a 3D grid of volumetric cells called voxels. Maps can be obtained in real-time without requiring an initial human-driven survey but their fidelity is constrained by the voxel grid resolution.

Recent works [15–18] have presented view planning approaches with both surface and volumetric representations. These represent the environment with a voxel grid but also extract an implicit Truncated Signed Distance Field (TSDF) [19] surface mesh to assess the map quality. Results show that these approaches can autonomously capture high-quality maps but maintaining multiple representations requires greater computation time and more parameter tuning.

This paper investigates an autonomous mapping system that uses SEE, a measurement-direct view planning approach. SEE can direct a sensor platform to obtain a detailed map of an environment without requiring an initial survey or imposing limits on the map resolution. It is combined with an accurate localisation approach and efficient path planning algorithm to create a complete autonomous mapping system.

III. PROPOSED APPROACH

Autonomous mapping systems are compromised of four primary components. Measurements are captured by a 3D sensor attached to a robotic platform. The measurements obtained from different sensor positions are integrated into a 3D map by tracking the movement of the sensor with a localisation approach. These views are chosen by a view planning algorithm to improve the map by capturing more detail from existing surfaces or observing new regions. Collision-free paths between views that can be traversed by the robot platform are found by a path planning approach.

A. Sensor Platform

This approach will use a DJI M600 drone as an aerial platform. This hexrotor drone has a flight time of up to 40 minutes and can lift a 6 kg payload. Mapping data is captured by a Frontier sensor system [20] mounted underneath the DJI M600 (Fig. 2). The Frontier is comprised of an Ouster OS1-64 LiDAR, an Intel RealSense D435i stereo depth camera and an Intel NUC computer kit. The Ouster LiDAR is the source of map measurements due to its long range. The

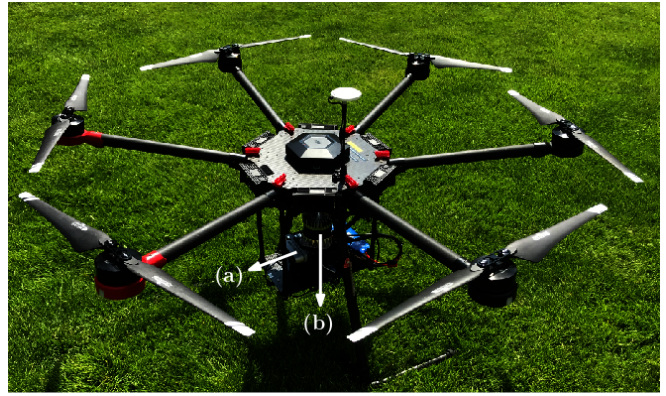


Fig. 2. Photograph of the DJI M600 aerial platform with a Frontier sensor system [20] mounted underneath it. The sensors used are an Intel RealSense D435i camera, (a), and an Ouster OS1-64 LiDAR, (b). Photograph courtesy of the Dynamic Robot Systems group at the Oxford Robotics Institute.

RealSense camera obtains visual data for the localisation approach. The Ouster LiDAR and RealSense camera both include an integrated Inertial Measurement Unit (IMU); the measurements from these are used by the localisation approach. The Intel NUC provides onboard processing to capture sensor data and run the localisation approach. The view and path planning approaches could also be run onboard the NUC if it is computationally feasible to do so.

B. Localisation

The sensor positions from which measurements are captured (i.e., views) need to be localised in a global reference frame before the measurements can be combined into a map. GPS is one of the most common methods for providing global localisation but it is often not accurate enough to create detailed maps and may not be available in some emergency response scenarios. More accurate and reliable localisation is obtained by using an odometry approach to track the movement of the platform from its starting location and referencing the view positions within this global frame.

Odometry approaches use sensor data to track the movement of a robotic platform. This data can include inertial measurements from an IMU, visual data from a camera and pointcloud data from a LiDAR sensor. Most approaches estimate motion using a combination of inertial measurements with either visual camera data [21–23] or point-based LiDAR data [24, 25]. Some recent approaches achieve highly robust estimates by using data from all three sensors [1, 26].

This mapping approach will use VILENS, a visual-inertial-lidar odometry system, to provide localisation. Experimental results presented in [1, 20] demonstrate that VILENS is the best performing odometry system among those evaluated. It is specifically designed to be used on the Frontier sensor system with data from the Ouster LiDAR, the RealSense camera and their integrated IMUs.

C. View Planning

An autonomous mapping system requires a view planning approach that can direct the sensor platform to improve

the 3D map of an environment without requiring human intervention. The proposed mapping system uses SEE, a measurement-direct view planning approach, to generate and select views by evaluating captured sensor measurements. SEE aims to obtain a minimum measurement density from all surfaces in an environment. This minimum density value can be set to ensure that the captured map is sufficiently detailed to be useful for an emergency scenario. SEE is able to rapidly capture highly complete maps by choosing efficient views that can provide the greatest improvement in map coverage while travelling the shortest possible distance.

D. Path Planning

The sensor platform must be able to safely navigate between views when building a map. Path planning algorithms use sensor measurements and obstacle information encoded in the map to plan collision-free paths between views. The path planning algorithms most commonly used by mapping systems are Rapidly-exploring Random Trees (RRT) [27] and RRT* [28]. These algorithm can reliably plan collision-free paths but typically require greater computation time than newer methods. The proposed mapping system uses AIT*, an almost-surely asymptotically optimal sampling-based planner, to efficiently compute collision-free paths between views. Experimental results show that AIT* can calculate such paths faster than RRT and RRT* [4, 5].

IV. SIMULATION RESULTS

The view planning performance of SEE has been evaluated experimentally in a realistic simulation environment on large-scale building models. Experiments were performed with models of the Statue of Liberty [29], the Radcliffe Camera in Oxford [30] and the Notre-Dame de Paris [31]. The models are scaled to fit within a 40 m bounding box. Sensor measurements are captured by a simulated LiDAR mounted underneath an aerial platform. Gaussian noise is added to the measurements to simulate sensor noise. These experiments do not address the localisation problem so the position of the sensor platform is specified in a global frame. AIT* is used to plan collision-free paths between the views.

The results show visualisations of the maps captured from the building models using SEE at different stages of completion (Fig. 3). They demonstrate that SEE directs the sensor platform to obtain highly complete and detailed maps of every building model. The map captured from the Notre-Dame de Paris model attains slightly lower surface coverage than the Statue of Liberty and Radcliffe Camera maps. This is due to the flying buttresses on the Notre-Dame de Paris model occluding the visibility of surfaces below them, which prevents measurements from being captured. Visualisations of the intermediate mapping stages are presented to show that SEE efficiently plans views to improve a map by ensuring that surfaces close to the initial view are captured first before extending the map until it encompasses the entire structure.

V. REAL WORLD EXPERIMENTS

Real-world experiments were conducted using an early prototype of the mapping system. In these experiments,

sensor measurements were captured by an Intel RealSense L515 LiDAR camera. Localisation for building the 3D maps was provided by VILENS. The views obtained were human-directed so SEE and AIT* were not used.

The experiments captured maps of two different natural cave formations in Bermuda (Fig. 4). One experiment was performed in a large cave with tall natural pillar formations. This cave was mapped using human-directed views by walking around the cave with a handheld RealSense LiDAR camera. The other experiment was conducted in a smaller cave that was only accessible via a 10 cm diameter surface entrance. The map of this cave was captured by mounting the sensor on a long pole and gradually lowering it into the cave while rotating the pole in order to capture every side.

The mapping results of these experiments demonstrate the localisation performance of VILENS and motivate this work on an autonomous mapping system. It is evident from the maps obtained that VILENS was able to successfully track the sensor movement between views. The maps are largely complete but do contain some gaps, particularly at the tops of the pillars in the large cave. The proposed mapping system would mitigate this issue by using SEE to plan views that can capture a minimum measurement density from all surfaces. Views planned to observe the tops of the pillars would also be reachable by an aerial platform. The map accuracy would be improved by using an Ouster LiDAR as it is typically more accurate than the RealSense LiDAR for longer distances.

VI. CONCLUSION

Navigating around structures in disaster scenarios can be a dangerous and challenging task for emergency responders. This task can be made safer and easier by using robotic sensor platforms to capture detailed maps of potentially dangerous structures before responders enter them. The maps can be used to evaluate the structures and identify which areas are accessible and which may pose risk to responders.

Sensor platforms are most useful when they can capture maps in real-time without requiring human intervention. This paper investigates an autonomous mapping system with these capabilities. The system will capture measurements with a LiDAR sensor mounted on an aerial platform. The VILENS odometry system will be used to localise the platform as it moves between view positions. These views will be planned using the SEE view planning approach. Collision-free paths between the views will be planned by the AIT* algorithm.

Simulation experiments demonstrate that SEE can direct a sensor platform to capture complete maps of buildings and AIT* can efficiently plan collision-free paths between views. Real-world experiments using an early prototype of the mapping system show that VILENS can successfully localise the sensor positions from which measurements are captured so that they can be combined into a 3D map. These results indicate that the mapping system discussed would be capable of autonomously obtaining detailed maps of structures in disaster scenarios to aid emergency responders.

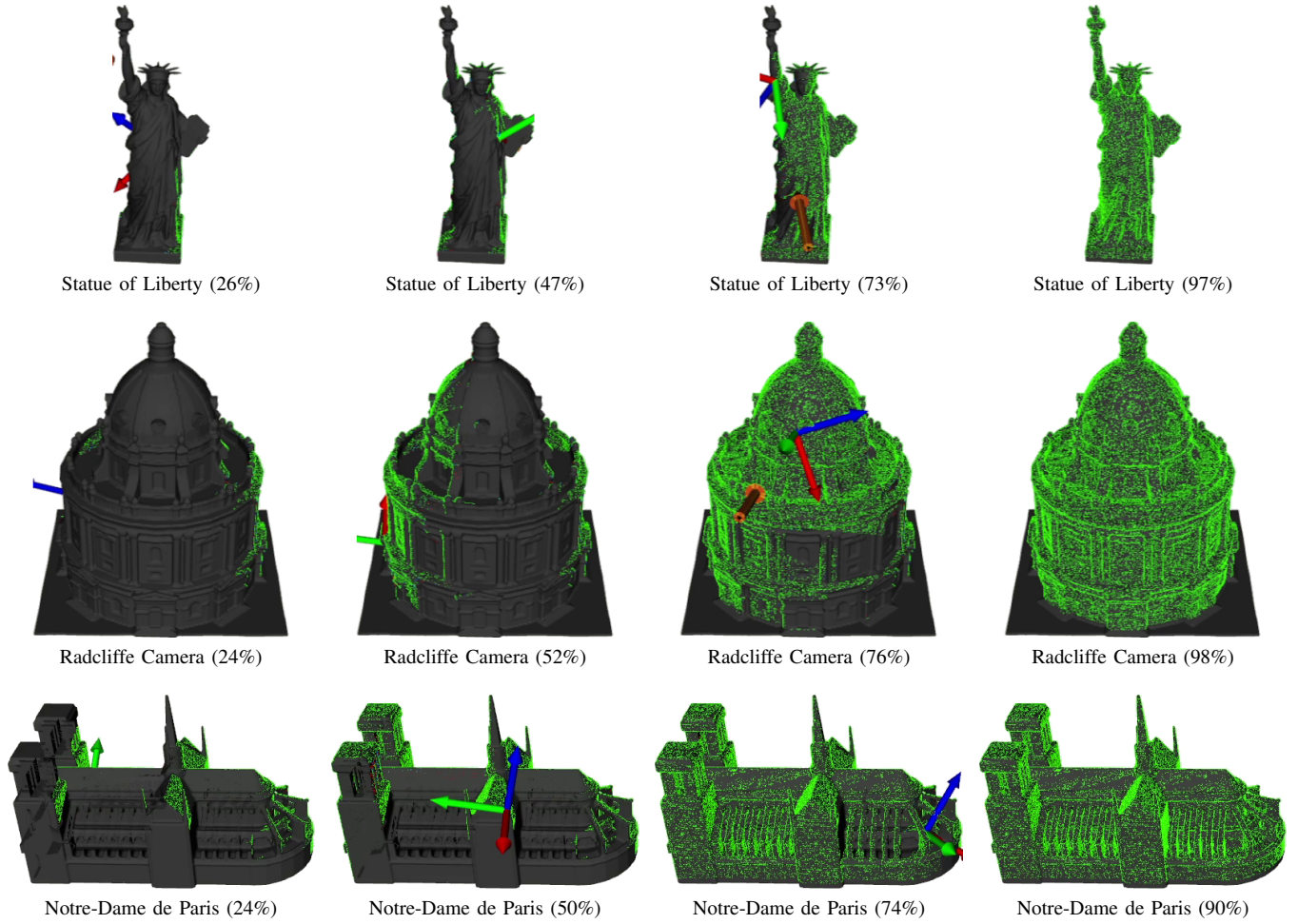


Fig. 3. Results demonstrating the view planning performance of SEE on building models in a realistic simulation environment. The image sequences show, from top to bottom, results for models of the Statue of Liberty [29], the Radcliffe Camera in Oxford [30] and the Notre-Dame de Paris [31]. The images in each sequence show the map obtained using SEE at different stages of completion. They were captured, from left to right, when the surface coverage attained by SEE was as close to 25%, 50%, 75% and 100% as possible. The green dots on the model surfaces denote sensor measurements. The RGB arrows, where shown, are coordinate frames representing the geometry of the model surface currently being observed by the simulated sensor platform. The orange arrow, where shown, indicates the current location of the sensor platform. The base of the models is not captured as sensor measurements within 1 m of the virtual ground plane were removed to prevent SEE from planning views below it. This is accounted for in the surface coverage calculations.

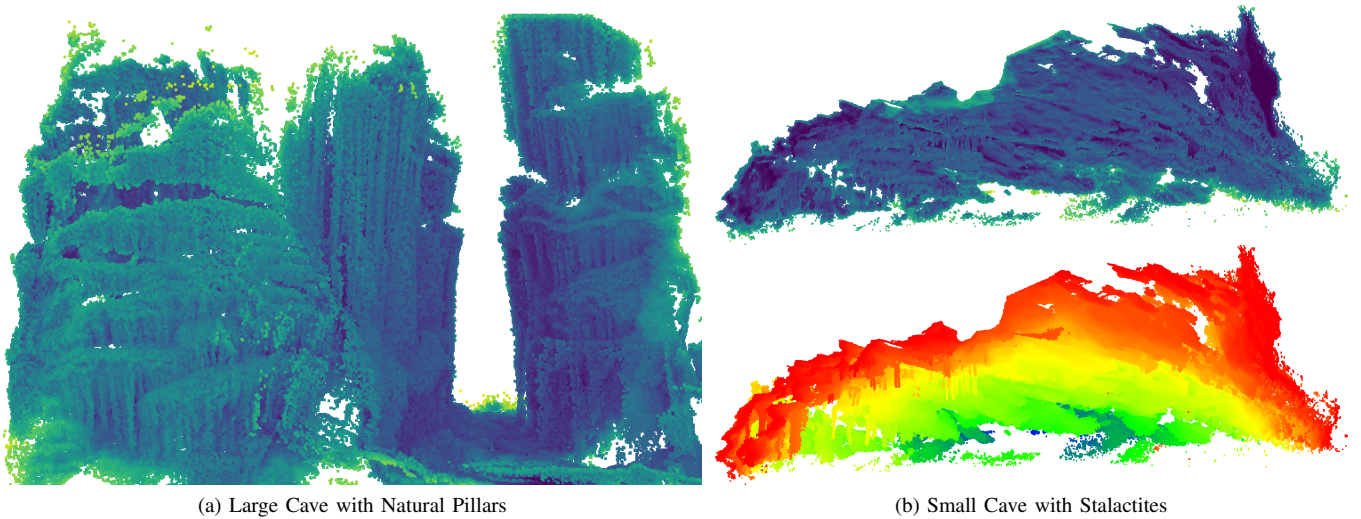


Fig. 4. Visualisations of maps obtained from two real-world caves using an early prototype of the mapping system. (a) shows a large cave with natural pillar formations. The map is coloured using an artificial illumination-based colourmap. (b) shows a vertical cross-section of a small cave with two colourmaps. The top image has an illumination-based colourmap and the bottom image uses a depth colourmap to better show the stalactites on the roof.

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