Autonomous Aerial Mapping for Construction

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***Abstract*— High-quality maps are important in the construction industry for conducting site surveys and building inspections but existing acquisition methods can be expensive, time consuming and require expert human operators. These maps could be captured more efficiently and cost effectively by using an autonomous aerial mapping system. Some commercial systems already exist but the capabilities of existing research platforms are more limited. The paper presents Osprey, an autonomous aerial system capable of mapping large outdoor structures without human intervention.**

I. Introduction

Capturing high-quality 3D maps of structures is important in the construction industry for surveying sites, monitoring the progress of building projects and assessing infrastructure integrity. Existing solutions typically require human experts to operate specialised survey equipment (e.g., Total Stations or Terrestrial Laser Scanners). These surveys can produce highly accurate maps but are often expensive and time consuming. If autonomous aerial mapping systems could obtain maps of similar quality, without requiring the time and expertise of a human operator, they would reduce the cost and complexity of capturing construction surveys.

Commercial systems (e.g., Skydio 3D Scan and Emesent Hovermap) have already demonstrated the efficacy of capturing high-quality structural maps with autonomous aerial platforms. They are being deployed to inspect critical infrastructure (e.g., cell towers and bridges), survey construction sites and map underground environments for mining applications. These commercial systems achieve state-of-the-art mapping capabilities by tightly integrating bespoke sensor payloads and aerial platforms with advanced mapping algorithms.

Research systems for autonomous aerial mapping have not yet demonstrated equivalent capabilities to these commercial systems. This is likely due to the complexity of developing and integrating the constituent components required to create a complete mapping system. An autonomous mapping system requires five key components: (i) a sensor payload to capture measurements, (ii) an odometry or localisation algorithm to estimate the platform pose, (iii) a mapping algorithm to aggregate measurements from different poses, (iv) a mission planner to decide where measurements should be captured from and (v) a motion planner to safely navigate the platform. Most existing work on autonomous aerial mapping focuses specifically on developing mission planning algorithms and is only evaluated in simulation or small indoor environments. Some aerial mapping systems have been demonstrated operating in larger real environments, both outdoors and underground (e.g., multiple teams in the DARPA SubT Challenge used autonomous aerial systems).

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Fig. 1. The Osprey autonomous aerial mapping system surveying a large industrial building.

This paper presents Osprey (Figs. 1 and 2), an autonomous aerial system whose constituent components have all been developed by labs in the Oxford Robotics Institute (ORI). The Osprey system uses an off-the-shelf DJI M600 drone as the base aerial platform and includes a custom sensor payload developed by our lab called Frontier [1]. It integrates the Visual Inertial Legged/Lidar Navigation System (VILENS) [2] algorithm for odometry, VILENS-SLAM [1] for mapping, the Surface Edge Explorer (SEE) [3] for mission planning and Adaptively Informed Trees (AIT*) [4] for motion planning. Field experiments with the Osprey mapping system demonstrate that it can autonomously map large buildings without human intervention.

The remainder of this paper is structured as follows. Section II presents an overview of related research on autonomous aerial mapping systems. Section III presents the Osprey system and its constituent components. Section IV presents the results of field experiments conducted with Osprey. Section V reviews the mapping capabilities of Osprey and discusses future work with the system.

II. Related Work

Most work on autonomous aerial mapping systems focuses on developing efficient mission planning algorithms. These are often only evaluated in simulation environments [3, 5–9] due to the complexity of integrating a mission planner into a complete autonomous mapping system. Some complete mapping systems are demonstrated on aerial platforms in small indoor environments [10–14] but their scalability to larger scenes is typically not demonstrated and may not be achievable without an external positioning solution (e.g., from a VICON system) [13, 14]. Complete aerial mapping systems have also been developed to map large underground [15–17] and indoor environments [18] using exploration-based mission planning.

Some autonomous aerial systems have been presented that can map outdoor environments [19–24]. Most of these use visual [19–21] or visual-inertial [22, 23] sensor payloads and obtain maps with visual reconstruction methods (e.g., multiview stereo). The captured maps are complete but the metric accuracy of these reconstructions is typically lower than LiDAR measurements. Yoder et al. [24] present a system using a sensor payload with a LiDAR, IMU and cameras that is similar to the one presented in this work.

This paper presents Osprey, an autonomous aerial mapping system that can capture maps of large outdoor structures without human intervention. The Osprey mapping system uses a sensor payload consisting of a LiDAR, IMU and stereo depth camera.

III. Osprey System

Autonomous aerial mapping systems are comprised of five key components. A sensor payload (e.g., with cameras, LiDARs and IMUs) mounted onto an aerial platform captures measurements. An odometry or localisation algorithm uses these sensor measurements to estimate the platform motion relative to a starting pose or identify its position in a global reference frame. A mapping algorithm integrates the measurements captured at different poses into a common reference frame and can correct for drift in the odometry system by identifying loop closures. A mission planner determines where the platform should capture measurements from so as to ensure coverage of all surfaces within a bounded region of space. A motion planner can then use an occupancy grid representation of the map to identify collision-free paths for the platform to traverse when moving between viewpoints. The following sections describe the implementations of each component used in the Osprey mapping system.

A. Sensor Platform

The Osprey mapping platform (Fig. 2) is comprised of an off-the-shelf DJI M600 drone and a custom Frontier [1] sensor payload. The DJI M600 is a hexrotor drone with an integrated flight controller, IMU and GPS receiver. It has a flight time of up to 30 minutes when carrying the 3 kg Frontier payload. The Frontier sensor payload combines an Ouster OS1-64 LiDAR, an Intel RealSense D435i stereo depth camera and an Intel NUC computer into a single device which is mounted onto the drone and powered from a battery. All processing is performed onboard the Intel NUC.

B. Odometry or Localisation

It is necessary to know the platform pose in a common reference frame when capturing sensor measurements in order to combine them into a consistent map. The platform pose can be determined either by estimating its motion relative to a starting position with an odometry algorithm or by identifying its location within a global reference frame using a localisation method (e.g., GPS). The Osprey mapping system uses the VILENS [2] odometry algorithm to estimate the platform pose as it provides better accuracy than GPS.

Fig. 2. Photograph of the Osprey aerial platform, a DJI M600 drone with a Frontier sensor payload mounted underneath it.

VILENS is a multi-sensor fusion odometry algorithm that can combine measurements from several different sensors (e.g., camera, IMU, LiDAR and GPS) into a factor graph representation to compute a single robust estimate of the platform's motion. The Frontier sensor payload can provide visual features from the RealSense camera and geometric features from the Ouster LiDAR while the DJI flight controller can provide IMU and GPS measurements. We experimentally evaluated different combinations of these sensor inputs with VILENS and determined that the best pose estimation was achieved by using geometric features from the LiDAR and inertial measurements from the IMU.

C. Mapping

The mapping component of an autonomous mapping system combines the measurements captured from different poses into a complete map of the environment. This map can be used by the motion planner to identify collision-free paths for the platform to traverse through the environment.

The Osprey mapping system uses VILENS-SLAM [1] to create a map of the environment as the drone moves between viewpoints chosen by the mission planner. New measurements are captured by the LiDAR and added to the map every $0.5\,\mathrm{m}$ in addition to at the chosen viewpoints in order to obtain a denser map. VILENS-SLAM uses a pose graph to represent both the measurements obtained and the pose they were captured from. When the platform returns to a location close to one previously visited, as determined by the VILENS odometry estimate, the pose graph is used to check for a loop closure by computing an Iterative Closest Point (ICP) alignment between the current measurements and the set of measurements associated with a nearby pose in the pose graph. If the computed alignment is valid then it can be added to the pose graph as a loop closure. This helps correct for odometry drift and produces a better combined map.

D. Mission Planning

The mission planner determines where the mapping system should capture measurements from in order to obtain a complete map of the environment. Most systems use a Next Best View (NBV) approach for mission planning which evaluates the current map and decides where measurements should be captured from next in order to best improve it.

The Osprey system uses SEE [3] for mission planning. SEE is a NBV approach that aims to capture a minimum measurement density from all surfaces in the environment. It generates viewpoint proposals to capture measurements from surfaces with insufficient density and extend its map into unobserved regions. Next best views are iteratively chosen from these proposed viewpoints to improve the map until the environment is completely observed. SEE maintains an internal map representation separate from the VILENS-SLAM map but utilises the same pose graph to take advantage of loop closure corrections from VILENS-SLAM.

E. Motion Planning

A motion planner is required to identify collision-free paths for the platform to move along between viewpoints chosen by the mission planner. Collisions are detected by using a voxel representation of the map to identify regions of occupied and free space.

The Osprey system uses AIT* [4], an almost-surely asymptotically optimal sampling-based planner, for motion planning. AIT* is able to plan efficient collision-free paths between viewpoints by finding an initial solution and then continuously improved it within the remaining budgeted planning time.

IV. Field Experiments

The mapping performance of the Osprey system is demonstrated qualitatively by experiments conducted on a large industrial building at the Fire Service College, Moreton-in-Marsh, United Kingdom. The structure is a standalone two-storey building approximately 28x14x13 m in size. Osprey was able to autonomously capture maps of the structure in multiple experiments. The mean mapping time for each experiment was 20 minutes and the mean distance traversed by the platform was 400 meters. In these experiments the mission planner was constrained to proposing viewpoints that would obtain a complete map between 3 and 10 m vertically in order to maintain a safe distance above the ground and ensure that the odometry system could provide a reliable pose estimate, which was not possible when flying above the building due to the LiDAR's limited vertical field-of-view.

Qualitative results present the flight path of the platform and the map captured by VILENS-SLAM during one of the experiments (Fig. 3). The loops in the flight path were caused by repeated attempts by the motion controller to reach a viewpoint due to adverse conditions (e.g., wind gusts). The map is presented with two textures: a height colourmap and with true colour overlaid from RealSense camera images. The true colour map has slightly less coverage than the height coloured map as not all points in the pointcloud could be assigned a colour from the camera images. A video of the experiment is available at `https://youtu.be/MphGpIPniOE`. These results show that the Osprey system was able to autonomously capture a map of the building that is complete within the bounding and visibility constraints of the mission planner.

V. Conclusions and Future Work

High-quality 3D maps of structures are important in the construction industry for inspecting and assessing building projects but existing solutions for obtaining them can be expensive and time consuming. Capturing maps with an autonomous aerial mapping system can make obtaining this data cheaper and easier. Some commercial systems already exist but the capabilities demonstrated by research systems are more limited. The Osprey mapping system presented in this paper demonstrates that it is capable of mapping large outdoor structures without human intervention.

Future work with the Osprey mapping system will focus on upgrading the sensor payload with a wider vertical field-of-view LiDAR for flying above buildings and multiple colour cameras to produce maps with better true colour. The robustness of the motion controller will be improved and multimission capabilities will enable the mapping of larger structures over multiple flights. Experiments with the new system will quantitatively compare the captured map with one obtained using survey equipment.

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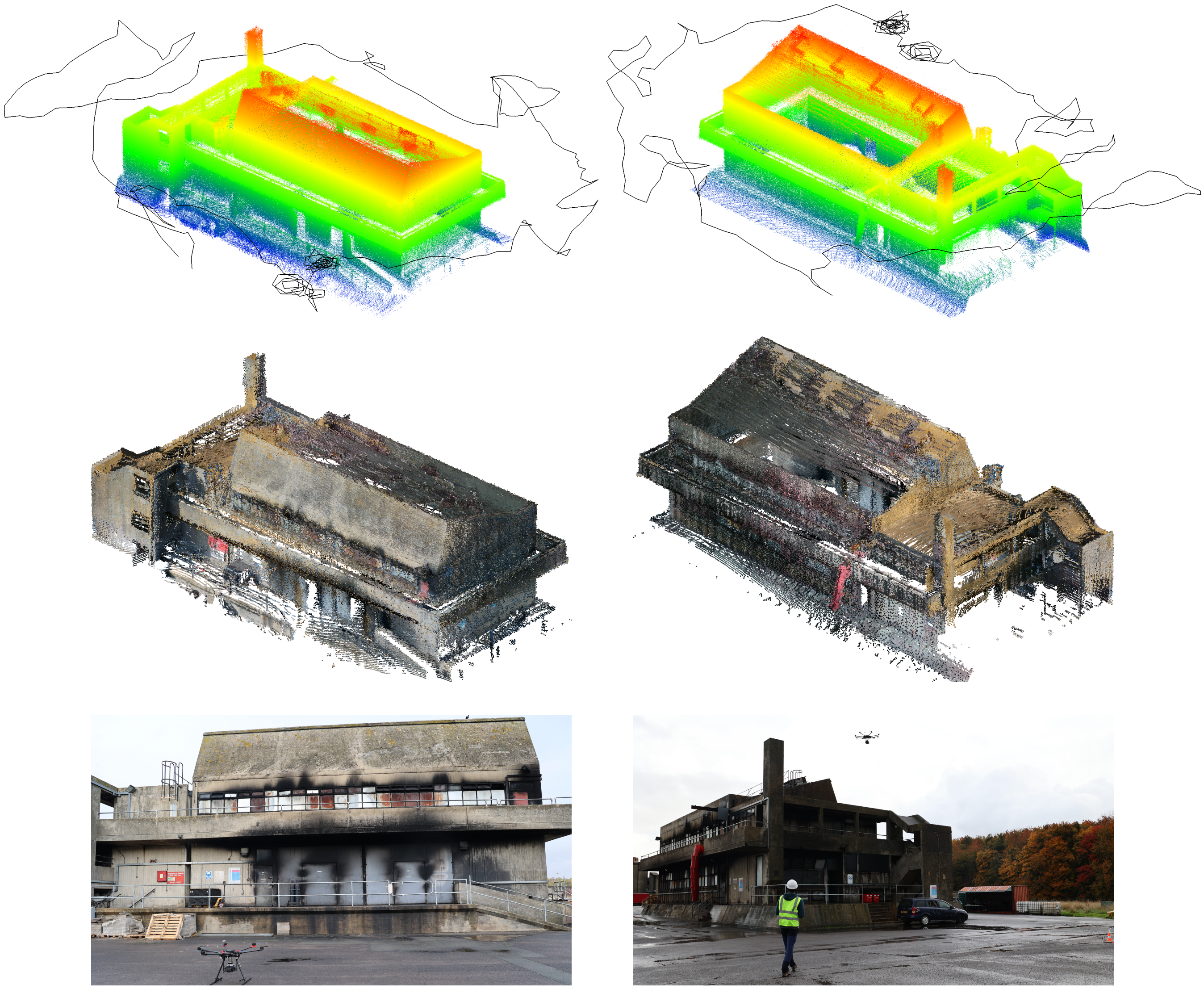

Fig. 3. Qualitative results from mapping a large industrial building at the Fire Service College, Moreton-in-Marsh, United Kingdom with the Osprey system. The images show, from two perspectives (left and right), the map obtained by VILENS-SLAM in one of the experiments textured with a height colourmap and the flight trajectory of the platform (top), the same map with true colour overlaid from RealSense camera images (middle) and photographs of the industrial building (bottom).

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