On the Advantages of Multiple Stereo Vision Camera Designs for Autonomous Drone Navigation

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Abstract—In this work we showcase the design and assessment of the performance of a multi-camera UAV, when coupled with state-of-the-art planning and mapping algorithms for autonomous navigation. The system leverages state-of-the-art receding horizon exploration techniques for Next-Best-View (NBV) planning with 3D and semantic information, provided by a reconfigurable multi stereo camera system. We employ our approaches in an autonomous drone-based inspection task and evaluate them in an autonomous exploration and mapping scenario. We discuss the advantages and limitations of using multi stereo camera flying systems, and the trade-off between number of cameras and mapping performance.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) deployed in everyday environments are facing increasingly complex scenarios and tasks. The problem of selecting which regions of the surrounding environment to attend to during visual exploration, search, and mapping tasks is computationally and energetically demanding. Therefore, UAVs should be endowed with efficient active perception mechanisms that allow them to attend to objects of interest while avoiding processing irrelevant sensory information. Furthermore, the design of systems with perceptual redundancy are of utmost importance in order to ensure safety and robustness to failures, since sensor arrays can significantly improve perceptual coverage, task-execution speed, and overall state estimation accuracy. Hence, the designer of the robotic system should carefully select an appropriate number and type of sensors, taking into account task performance as well as on-board resource-constraints. High perceptual coverage for safe navigation and mapping of real world scenarios can be achieved using a flying drone vehicle equipped with vision and IMU systems. Using multiple cameras and IMUs offers a robust solution. However, it comes at the cost of increased payload, and additional computational power and processing-time requirements. In this work we asses the viability of multi-stereo-camera UAV (see Fig. 1) for autonomous inspection tasks, combining state-of-the-art simultaneous localization and mapping (SLAM) techniques, with cost-efficient NBV exploration algorithms [1], to geometrically reconstruct and label all objects in man-made environments. Our navigation system is targeted at multi-camera UAVs, includes probabilistic semantic-metric mapping representations, and uses a RRT planning algorithm that leverages both semantic and metric information for autonomous visual data collection. Our target application is the inspection of man-made structures, requiring minimal human intervention. Throughout the rest of this article we overview the proposed system design and perform an evaluation of the advantages and disadvantages of using multi-camera systems using UAVs, from a computational and mapping performance perspective. This work assesses the former problem trade-offs on an UAV-based exploration and mapping scenario.

II. METHODOLOGY

In the rest of this section we describe the proposed multi-stereo-camera system and methodologies for active exploration and semantic-metric mapping of man-made infrastructures.

A. System Overview

The proposed system for autonomous navigation tasks consists of a UAV specifically designed for mapping tasks,
that comprises multiple cameras, Inertial Motion Units (IMUs), and an altimeter. Our navigation system relies on an off-the-shelf SLAM system with loop closing and relocalization capabilities [2], which is fed with RGB-D data provided by user-selected cameras and IMUs measurements. These are fused using an extended Kalman filter (EKF) for improved robustness on self-motion tracking performance. In the proposed hardware design we attempt to minimize weight to achieve better flight performance and flight duration until battery depletion, while at the same time minimizing the size of the parts to avoid vibrations, and ensure camera sensors can be placed in orthogonal directions to maximize visual coverage. Our model adds camera sensors to the quad base frame (DJI F450), together with a battery mount for easy battery replacement. We use Jetson Xavier NX as our on-board computer and the Pixhawk 4 as the low-level flight controller. Furthermore, the system comprises a set of stereo-camera sensors (Zed 2 and Mini cameras) suitable for visuo-inertial based navigation which are rigidly attached to the UAV body base frame, and whose poses are assumed deterministically known with respect to the base frame, from the kinematics model.

1) Multi-camera Navigation System: We rely on a probabilistic observation model that combines metric and semantic visual cues, which are efficiently fused in a volumetric octogrid structure [3], and a NBV planner that leverages both geometric and semantic information for task-dependent exploration. We use an octomap representation and recursive Bayesian volumetric mapping to sequentially estimate the posterior probability distribution over the map, given sensor measurements and sensor poses obtained through the robot kinematics model and an off-the-shelf SLAM module. Our method for semantic segmentation relies on a Deep Convolutional Neural Network (DCNN) encoder-decoder segmentation network, that receives RGB or grayscale images as input, and outputs a probability distribution over the known object categories for each pixel \((u, v)\). We use BiseNet [4] because it is compact, fast, robust and easy to use, being suitable for remote sensing applications running on embedded systems (e.g. UAVs) with low computational specifications. For each pixel \((u, v)\), the network outputs a probability distribution \(p^c(u, v) \in \mathcal{P}^{K_c}\) over the set of known classes \(C\), where \(K_c\) represents the number of known classes. For training the network we use a combination of real and simulated (AirSim) annotated datasets, and the categorical Cross-Entropy loss function. At run-time, the semantic probability distribution over all classes and image pixels is merged with the corresponding depth image to obtain a semantically labeled point cloud, using a known extrinsic calibration parametric model.

III. Results

A. Multi-camera Navigation System

In order to be able to quantitatively and qualitatively measure the performance of the proposed mapping and planning approaches, a realistic shipyard environment (see Fig. 3a) was created using the Gazebo simulator [5]. The environment consists of a dry-dock. An intelligent active mapping algorithm should maximize task-related rewards, in this case information gathering, by focusing on rewarding viewing directions. In each experiment we let the observer collect \(T = 2000\) observations (i.e. sense, plan and act iterations). Each experiment was repeated 10 times to average out variability in different simulations, due to the randomized nature of our algorithm, and non-systematic errors influenced by multiple simulation factors.

We first analyzed the influence of different camera setups in the trade-off between reconstruction accuracy, planning, and run-time performance. For the number of cameras, we considered \(M \in \{1; 3; 5\}\). Fig. 3 demonstrates the advantages of utilizing multiple cameras placed around the UAV. For this particular scenario, on average, the use of multiple cameras not only improves occupancy but also the time-to-full-coverage. However, the cameras placed on the back and bottom provide lower long-term information when compared to the front and lateral cameras, since most of the surrounding environment is covered by the latter while the system is moving.

B. Multi-Camera Drone Hardware Design

In order to select the most suitable camera configuration for our autonomous flying system, we measured battery power consumption and time-to-full-coverage across multiple designs (i.e. different number of sensors) while hovering...
the real UAV with a different number of cameras (for 5 different runs). As can be seen in Fig. 4, the power consumption (proportional to lithium battery voltage) increases with the number of cameras since they increase both the weight and processing requirements of the system. Hence, although higher visibility and faster coverage can be achieved with more cameras ($M = 5$), when considering power constraints and flight duration (Table. I), $M = 3$ is a more appropriate design choice for this use-case.

**IV. CONCLUSIONS**

In this work we have proposed and assessed multi-stereo camera setups for autonomous navigation of UAVs that incorporates probabilistic semantic-metric mapping representations, for semantically-aware NBVs planning. We assessed the proposed designs and methodology on a realistic simulation environment (Gazebo), and evaluated the trade-offs of using multi-camera navigation systems in UAV-based inspection tasks. Our final design choice considered power, computation requirements and flight-time duration, in a real experimental setup. In the future we intend to improve the proposed multi-camera approach with the ability to schedule sensor acquisition such as to decrease computational load and power consumption.

**ACKNOWLEDGMENT**

The authors would like to acknowledge the financial contribution from Smart Industry Program (European Regional Development Fund and Region Midtjylland, grant no.: RFM-17-0020). The authors would further like to thank Upteko ApS for bringing use-case challenges.

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**TABLE I:** Hovering time until battery depletion (minutes).

| Cameras | $M = 1$ | $M = 3$ | $M = 5$ |
|---------|---------|---------|---------|
| Flight Time | 8.19 ± 0.86 | 8.17 ± 0.41 | 6.00 ± 0.99 |