

Real-time Generation of 3-Dimensional Representations of Static Objects using Small Unmanned Aerial Vehicles

Pau Talarn*

NaNoNetworking Center in
Catalunya (N3Cat), Universitat
Politècnica de Catalunya, Spain
pau.talarn@estudiantat.upc.edu

Bernat Ollé*

NaNoNetworking Center in
Catalunya (N3Cat), Universitat
Politècnica de Catalunya, Spain
bernat.olle@estudiantat.upc.edu

Filip Lemic†

AI-driven Systems Lab, i2Cat
Foundation, Spain
filip.lemic@i2cat.net

Sergi Abadal

NaNoNetworking Center in
Catalunya (N3Cat), Universitat
Politècnica de Catalunya, Spain
sergi.abadal@upc.edu

Xavier Costa Perez

AI-driven Systems Lab, i2Cat
Foundation, Spain; NEC Laboratories
Europe, Germany; ICREA, Spain
xavier.costa@i2cat.net

ABSTRACT

Recent advances in robotics and nanotechnology resulted in a set of miniaturized Unmanned Aerial Vehicles (UAVs). Such small UAVs are envisioned to operate in hard-to-reach areas for enabling applications such as structural monitoring or content capturing. Towards showcasing this vision, we demonstrate a small UAV-supported setup for real-time autonomous generation of 3-Dimensional (3D) representations of static objects. In the setup, a small UAV (i.e., CrazyFlie 2.1) is envisioned to visit a set of locations, acting as a carrier and power source of a camera sensor. At each location, the sensor is expected to take a picture of the object and report it to the station. The station implements a pipeline for 3D reconstruction of the object based on its pictures taken by the UAV.

ACM Reference Format:

Pau Talarn, Bernat Ollé, Filip Lemic, Sergi Abadal, and Xavier Costa Perez. 2023. Real-time Generation of 3-Dimensional Representations of Static Objects using Small Unmanned Aerial Vehicles. In *Proceedings of ACM Conference (Conference'17)*. ACM, New York, NY, USA, 3 pages. <https://doi.org/10.1145/nnnnnnn.nnnnnnn>

1 INTRODUCTION

Recent advances in robotics resulted in a rapid uptake of the Unmanned Aerial Vehicle (UAV) technology [4]. At the same time, recent advances in nanotechnology are driving the miniaturization of advanced systems such as UAVs [1]. This resulted in miniaturized systems known as small UAVs, such as the CrazyFlie 2.1 depicted in Figure 1. Small UAVs are opening the space for a novel line of

applications targeting hard-to-reach areas for automatizing structural monitoring, generating Virtual Reality (VR) content, etc. An additional benefit of small UAV systems comes from the fact that they are mainly envisioned to be utilized indoors and, as such, they will mostly not require flight licenses. They are, therefore, more interesting from the average user perspective than the outdoor UAVs and, hence, feature a higher scaling potential and market uptake.

One application that has relatively recently generated a significant interest is the digital reconstruction of 3-Dimensional (3D) objects [7], finding its utility advertisement, gaming, hospitality, etc. Although we are witnessing a surge of such applications on devices such as smartphones, they still require manual interventions, e.g., taking pictures from different angles, to be able to generate 3D object representations. As such, these approaches consume time and effort, consequently not scaling well.

In contrast, in this demonstration we show that such applications can be enabled through the utilization of small-scale UAVs. In particular, we demonstrate an open-source pipeline consisting of a small UAV acting as a carrier and power source of a Red, Green and Blue (RGB) camera sensor. The UAV can sequentially visit a set of locations around the object of interest and hover at each of them for taking a picture of the object. This is followed by the picture being transferred wirelessly to a station that features an open-source pipeline for generating a 3D representation of the target object. The sequence of locations to be visited by the UAV is determined dynamically based on the current features of the generated representation (i.e., a pointcloud) of the object.

2 SYSTEM DESIGN AND IMPLEMENTATION

System Design. The setup for the generation of 3D representations of static objects is depicted in Figure 2. We envision the UAV to be positioned for take-off facing the object. The generation of 3D reconstruction is then triggered from the station, which results in the UAV taking off and capturing the first pictures. We use an RGB camera sensor soldered on the UAV for capturing the pictures. The utilized camera sensor system also features a WiFi transceiver, which is used for communication with the station (i.e., requesting the system to take a picture and transmitting picture to the station).

*The authors contributed equally to this work.

†Corresponding author.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Conference'17, July 2017, Washington, DC, USA

© 2023 Association for Computing Machinery.

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM... \$15.00

<https://doi.org/10.1145/nnnnnnn.nnnnnnn>

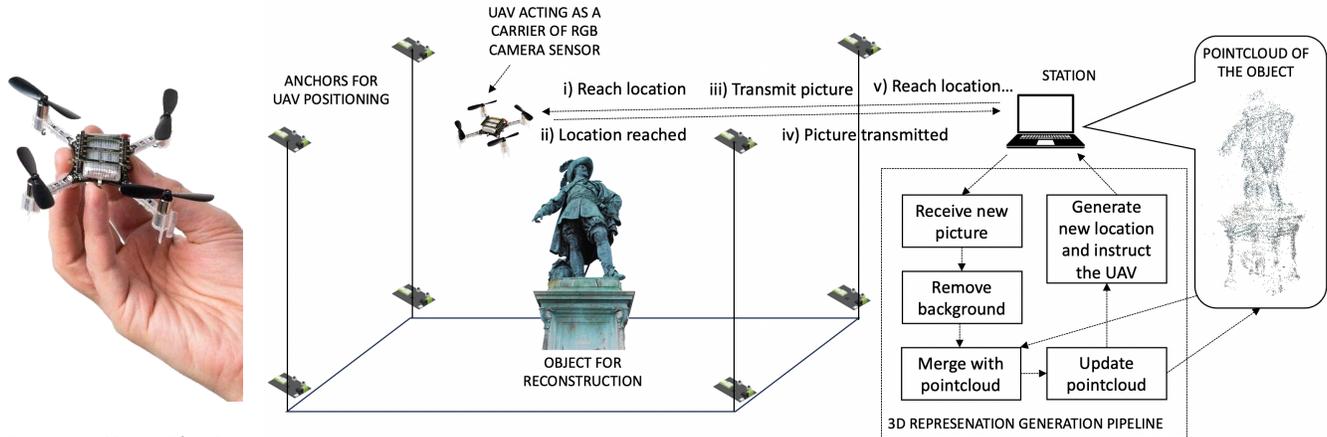


Figure 1: CrazyFlie 2.1

Figure 2: Setup for small UAV-supported generation of 3D object representations

Two images taken from two different locations are needed for producing the initial pointcloud representation of the object, hence the UAV is initially instructed to take two images of the object directly in front of it, with a slight drift in the locations. The pointcloud is then generated using the well-known Structure from Motion (SfM) approach [6]. The pointcloud generation is preceded by the background removal from the pictures, as it is well known that the background features negatively affect the pointcloud generation accuracy. The SfM algorithm operates on the principle of obtaining the location and orientation of a monocular camera with respect to a target object, based on which it is able to reconstruct the object.

Based on the available pointcloud, we utilize the Kernel Density Estimation (KDE) algorithm for deciding on the next location to be visited by the UAV. The KDE algorithm uses a mixture consisting of one Gaussian component per point, resulting in an essentially non-parametric estimator of density. The intuition behind this approach is to minimize the time needed for obtaining satisfactory pointcloud quality by positioning the UAV in a way that covers the pointcloud regions with lowest density.

System Implementation. We utilize Crazyflie 2.1 UAV in our demonstration, primarily as it is an open hardware and software platform. Crazyflie 2.1 UAVs come with a FreeRTOS operating system and a Bluetooth LE transceivers for control. They also feature an accelerometer, gyroscope, magnetometer, high precision pressure sensor, and two expansion boards for capability extensions. In this work, one expansion slot is utilized for the Loco Positioning System (LPS) tag, while the RGB camera sensor (i.e., an ESP32-CAM system) is connected solely to the powering pins of the UAV.

We use the Crazyflie's LPS to provide accurate indoor positioning. The system consist of a tag to be localized and multiple anchors distributed over the volume used for localizing the tag. The system can be deployed by simply positioning of the anchors, measuring their coordinates relative to a chosen origin, and initializing their automated calibration for synchronizing their transmission schedules. Once the anchors are self-calibrated, they can be used for localizing the UAV and consequently for its navigation toward the instructed locations. Given that the system for 3D reconstruction is relying solely on physical deployment, localization, and initiation of the self-calibration of the anchors, we argue that it can be rapidly deployed in new environments.

The LPS tag Decawave 1000 uses Ultra Wide-Band (UWB) technology for communication and localization. The tag can estimate its location based on the UWB signals received from the anchors, where the localization is performed using the Time Difference of Arrival (TDoA) procedure. A Crazyflie equipped with an LPS deck makes use of an extended Kalman filter to estimate its orientation and position, with its implementation based on [5]. The utilized system with 8 anchors is able to localize the tag in a 3D space with cm-level accuracy at the range of about 10 m [2, 3].

Software control of the UAV is done through an application that makes use of the Crazyflie Python library. It runs the following sequence: i) initialization and UAV take-off, ii) taking two pictures with a small offset in location, iii) sending pictures for pointcloud generation, iv) move to the next waypoint (defined as an $\langle x, y, z \rangle$ tuple) based on the quality of the currently generated pointcloud, v) taking and transmitting a new picture, etc. Communicating with and controlling the Crazyflie remotely can be done using a custom USB dongle called the Crazyradio, which provides 126 channels (2400 MHz - 2525 MHz) and works with the custom Crazyradio RealTime Protocol (CRTP) to communicate with the UAV.

3 CONCLUSION

In this demonstration^{1,2}, we will showcase a system for small Unmanned Aerial Vehicle (UAV)-supported autonomous real-time generation of 3-Dimensional (3D) representations (i.e., pointclouds) of static objects. Our aim is to receive an early community feedback on the system, given that we envision it as a driver for our future research. In particular, we envision eventually switching from a camera sensor to high-frequency antenna array that can provide comparable pointcloud generation performance, yet with by-design benefits along the lines of reduced energy consumption, privacy preservation, and reduced communication latency. Moreover, features such as dynamic obstacle avoidance and in-fleet operation are envisioned to be introduced. In terms of the vision, we argue that such an enhanced system will eventually be able to autonomously generate accurate real-time 3D representations of moving objects and people, providing a primer for a novel set of applications (e.g., person capturing system for fully-immersive Virtual Reality (VR)).

¹Demonstration video: to be provided at the camera-ready stage.

²Code repository: https://bitbucket.org/bernat-i2cat/3d_reconstruction/src/master/

REFERENCES

- [1] Filip Lemic et al. 2021. Survey on terahertz nanocommunication and networking: A top-down perspective. *IEEE Journal on Selected Areas in Communications* 39, 6 (2021), 1506–1543.
- [2] Ken Mendes et al. 2020. Automated, autonomous, and repeatable wireless experimentation in heterogeneous 3D environments: demo abstract. In *Embedded Networked Sensor Systems (SenSys)*. ACM, 601–602.
- [3] Ken Mendes et al. 2022. Small UAVs-supported Autonomous Generation of Fine-grained 3D Indoor Radio Environmental Maps. In *Distributed Computing Systems Workshops (ICDCSW)*. IEEE, 296–301.
- [4] Mohammad Mozaffari et al. 2021. Toward 6G with connected sky: UAVs and beyond. *IEEE Communications Magazine* 59, 12 (2021), 74–80.
- [5] Mark W Mueller et al. 2015. Fusing ultra-wideband range measurements with accelerometers and rate gyroscopes for quadcopter state estimation. In *Robotics and Automation (ICRA)*. IEEE, 1730–1736.
- [6] Onur Özyeşil, Vladislav Voroninski, Ronen Basri, and Amit Singer. 2017. A survey of structure from motion. *Acta Numerica* 26 (2017), 305–364.
- [7] Elisavet Stathopoulou et al. 2019. Open-source image-based 3D reconstruction pipelines: Review, comparison and evaluation. *Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-2/W17* (2019), 331–338.