A Revolutionary Idea for 3D Mapping using Unmanned Aerial Vehicle (UAV) with Raspberry Pi Camera Module

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Abstract

Nowadays, smart technologies are an important part of our daily lives in indoor and outdoor environments. Several smart devices are very user-friendly to set up, and they can be integrated and embedded with other sensors at a meager cost The Raspberry Pi is a credit card-sized computer that can be used as a full-featured computer by connecting it to a monitor or TV. It comes with Raspberry Pi OS, a customized version of Linux, and is equipped with a specialized processor, memory, and graphics driver. Raspberry allows the install an internal camera called Raspberry Pi Camera Module, both in the RGB band and NIR (Near-Infrared) band. This system's main advantages are its limited cost, its lightweight, and its simplicity in being used and embedded. The drone's pose stabilization and ability to navigate through outdoor spaces provide accurate data for 3D reconstruction. This paper will present how to make an Unmanned Aerial Vehicle for 3D mapping with the Raspberry Pi Camera Module.

Keywords: UAV, Python, Raspberry Pi, Raspberry Pi Camera, 3D scanning

1. Introduction

Over the past decade, unmanned aerial vehicles (UAVs) have experienced significant growth, particularly in civilian and military applications and cooperative air and ground surveillance, among others. UAV has garnered attention for topographic mapping due to its cost-effectiveness, superior quality, and adaptability for mapping relatively small-distributed areas. However, challenges such as designing for limited payload space, weight considerations, adjusting photogrammetric systems in UAV bodies, operational aspects during take-off, flight, and landing, data processing issues, and flight limitations persist [1].

Unmanned aerial vehicles (UAVs), commonly known as drones, have seen rapid adoption in recent years for civilian and commercial applications such as surveillance, inspection, and mapping. One area that has significantly benefited from UAV technology is 3D mapping, which aims to create detailed 3D models of objects or environments [2]. UAVs with cameras can efficiently capture images of an area from multiple angles above the ground. These images can then be processed using techniques to construct intricate 3D maps [2]. We use this system to generate 3D maps that provide actionable insights for various use cases like urban planning, construction monitoring, and disaster response.

Our work has the following structure. First, we provide the necessary background on UAV, Raspberry Pi systems, and related 3D mapping algorithms. Next, we describe our methodology, including UAV and sensor selection, integration with the Raspberry Pi camera module, flight pattern configuration, and 3D reconstruction processing pipeline. Key results demonstrate the accuracy of models built using images collected by our system. Finally, we discuss applications of our low-cost UAV-based solution for 3D modeling along with future work to enhance mapping efficiency and scalability.

Here are some of the critical applications and future needs for 3D mapping using, especially with unmanned aerial vehicles (UAVs):

Real-life Applications:

- Topographic Mapping - Highly detailed elevation models for terrain analysis, land surveying, geology, and civil engineering projects.
- Urban Planning - Precise 3D city models to plan transportation networks, monitor urban sprawl, design zoning, etc.
- Architecture & Construction - As-built documentation of buildings and tracking construction progress over time.
- Disaster Management - Rapid scanning of damage and efficient allocation of relief resources after natural calamities.
- Agriculture & Forestry - Monitoring crop growth and health diagnosis using multispectral data and calculating biomass.
- Archaeology & Preservation - Creating 3D maps of excavation sites, historical monuments, and cultural heritage sites.

Applications in the UAV Sector:

- Infrastructure Inspection - Hard-to-reach structures like bridges, wind turbines, cell towers, etc.
- Public Safety & Security - Crime scene reconstruction, optimizing patrols, real-time surveillance.
- Industrial Automation - Monitoring mining sites, oil and gas facilities, power plants, etc.
- Logistics & Transportation - Surveying proposed routes for roads, railroads, pipelines, etc.

Future Needs:

- Higher resolution - More detailed textures and elevation models with sub-cm accuracy.

- Increased automation - Reducing manual image processing through AI and deep learning.
- Multi-modal data fusion - Thermal or hyper spectral sensors.
- Enhanced analytics - Extracting actionable information from 3D maps via computer vision techniques.
- Platform and sensor miniaturization - Deploying nano-UAVs and smaller cameras for indoor uses.
- Scalability and standardization - Cloud processing pipelines and data formats compatible across software.

Related work

Abraham E. Karem is regarded as the founding father of UAV (drone) technology. He built his first drone during the Yom Kippur War for the Israeli Air Force [10]. Indian Institute of Technology (IIT) Bombay - The R&D group ANPaC Labs has worked on drone-based 3D mapping and localization algorithms. Prof. K.S. Venkatesh and his team focus on UAV imaging systems. Professor K.S. Venkatesh heads the Aero Imaging Lab in the Department of Mechanical Engineering. Some of his team's relevant projects include Developing UAVs for remote sensing applications like vegetation mapping, water body identification, etc., using RGB and multispectral imagery and experimenting with lightweight payload design for UAVs to carry multiple sensors and validation through applications like precision agriculture. Work on SLAM (simultaneous localization and mapping) algorithms for micro aerial vehicles in GPS-denied environments [11].

The work in this paper includes two applications: 1) Building Information Modeling (BIM), in which 3D models are used to create digital representations of buildings, facilitating design, construction, and facility management. 2) Enhanced Perspectives and Insights in which our ortho mosaic maps and 3D models provide capabilities like temporal change detection, volume and height analytics, and integration with other sensor data. This unlocks vital intelligence for decision support across agriculture, security, urban planning, etc.

2. Methodology

This thesis outlines a methodology for developing a UAV-based 3D mapping system. Objectives include creating a high-resolution terrain model and assessing accuracy. The study focuses on a chosen area, using a fixed-wing UAV and optimizing flight parameters for image capture. Data processing involves geo-referencing, ortho-rectification, and color correction. Photogrammetric processing utilizes SfM and MVS algorithms with industry-standard software. Photogrammetric processing will utilize Structure from Motion (SfM) and Multi-View Stereo (MVS) algorithms implemented through industry-standard software. Quality control measures, including visual inspection and validation against ground truth data, will be enforced. Quality control measures, GIS integration, and ethical considerations are included. The methodology concludes with planned quantitative analyses. While a planned approach, adjustments will be made based on practical considerations during implementation.

3. Experimental results

It was performed with the camera in the vertical orientation, providing a degree of overlap of 70% in the routine direction. The small height of the flight (12m) allowed them to have a very small GSD (0,5 cm). Since there was to evaluate the acquisition accuracy of the Ublox M8T device mounted on the payload and used to geo reference the images, external markers were used as Ground Control Points (GCPs) to reference the photogrammetric model. 13 photogrammetric markers were put on the ground of the flight field **(Figure 1).**

Figure 1: Marker placed on the ground (A) and a structure in elevation (B). **(Marco Piras, Nives Grasso, Ansar Abdul Jabbar; 2017, Pg.291)**

The markers were measured using the RTK (Real-Time Kinematic) approach. Their positions were determined with a centimetre accuracy. These points were used as references to orient the point clouds and as checkpoints to analyze the accuracy of the results; therefore, they were realized in a standard reference system with the measurement of the Ublox M8T (WGS 84).

IMU data processing: IMU sensors have systematic errors that require calibration to compensate for temperature drift, scaling factor, and angle misalignments. Calibrated values are provided for the Microstrain 3DM-GX3-35 IMU, but further calibration is necessary to measure the effects of UAV rotors. The noise and magnetic field of the rotors enhance the IMU's systematic errors. Data is collected with the IMU mounted on the UAV, both with and without the rotors running, to analyze the impact of the rotors. The standard deviations increase for all parameters when the rotors are on, indicating the effect of rotor noise.

The following table **Table 1.** shows the Mean and SD values of inertial sensor values with UAV rotors off and on with static position. . **(Marco Piras, Nives Grasso, Ansar Abdul Jabbar; 2017, Pg.292)**

	UAV rotors OFF	UAV rotors ON
Mean Roll	0.004 rad	0.013 rad
SD Roll	0.0005 rad	0.005 rad
Mean Pitch	-0.040 rad	-0.037 rad
SD Pitch	0.002 rad	0.003 rad
Mean Yaw	0.313 rad	0.294 rad
SD Yaw	0.002 rad	0.007 rad
Mean Accel_X	-0.042 g	-0.039 g
SD Accel_X	0.003 g	0.012 g
Mean Accel_Y	-0.006 g	-0.013 g
SD Accel_Y	0.0009 g	0.012 g
Mean Accel_Z	-1.003 g	-1.002 g
SD Accel_Z	0.001 g	0.046 g
Mean Gyro_X	-0.0005 g	0.0002 rad/s
SD Gyro_X	0.003 rad/s	0.027 rad/s
Mean Gyro_Y	0.0007 rad/s	0.0002 rad/s
SD Gyro_Y	0.003 rad/s	0.046 rad/s
Mean Gyro_Z	0.0003 rad/s	0.0007 rad/s
SD Gyro_Z	0.003 rad/s	0.014 rad/s
Mean Magn_X	0.217 Gauss	0.218 Gauss
SD Magn_X	0.001 Gauss	0.002 Gauss
Mean Magn_Y	-0.063 Gauss	-0.057 Gauss
SD Magn_Y	0.001 Gauss	0.003 Gauss
Mean Magn_Z	0.328 Gauss	0.331 Gauss
SD Magn_Z	0.003 Gauss	0.0027 Gauss

The noise from UAVs can be minimized using tools like Wavelet Analyzer toolbox in MATLAB.

Table 2. compares standard deviation values of the original signal, including noisy and de-noised signals. It can be seen that after de-noising the signal, there is a significant decrease in the standard deviation value for all inertial sensor values. This de-noising signal data can be integrated with GNSS data to improve the position quality. **(Marco Piras, Nives Grasso, Ansar Abdul Jabbar; 2017, Pg.294)**

	SD Values with a noisy signal	SD Values with de-noise signal
SD Roll	0.033 rad	0.029 rad
SD Pitch	0.051 rad	0.028 rad
SD Yaw	1.888 rad	0.949 rad
SD Accel_X	0.070 g	0.053 g
SD Accel_Y	0.037 g	0.030 g
SD Accel_Z	0.045 g	0.043 g
SD Gyro_X	0.117 rad/s	0.113 rad/s
SD Gyro_Y	0.123 rad/s	0.114 rad/s
SD Gyro_Z	0.376 rad/s	0.290 rad/s
SD Magn_X	0.163 Gauss	0.085 Gauss
SD Magn_Y	0.168 Gauss	0.086 Gauss
SD Magn_Z	0.019 Gauss	0.015 Gauss

Our focus is aligned with the work previously carried out by Marco Piras, Nives Grasso, and Ansar Abdul Jabbar. However, we have added some unique features to enhance the overall functionality. These additional features will provide users with an improved experience and more advanced capabilities beyond what has been previously accomplished. The additional features are:

Feature 1: Our technology generates 3D representation of areas, providing valuable insights for decision-making in industries such as agriculture, security, and urban planning. The system detects changes, performs volume analytics, and integrates sensor data for accurate analysis. Here, we first select a field that is somewhat isolated from much civilization (Figure 2); the Second thing is that with the use of Mission Planner Software, an orientation of the field is performed (Figure 3), and the fourth and last process marks the different areas of the field as per the requirements (Figure 4).

Figure 2: Field chosen as test area

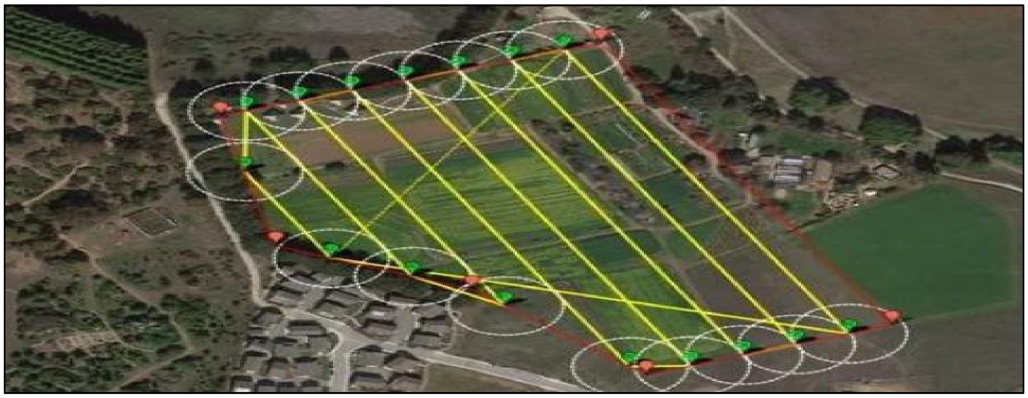

Figure 3: Orientation of test area

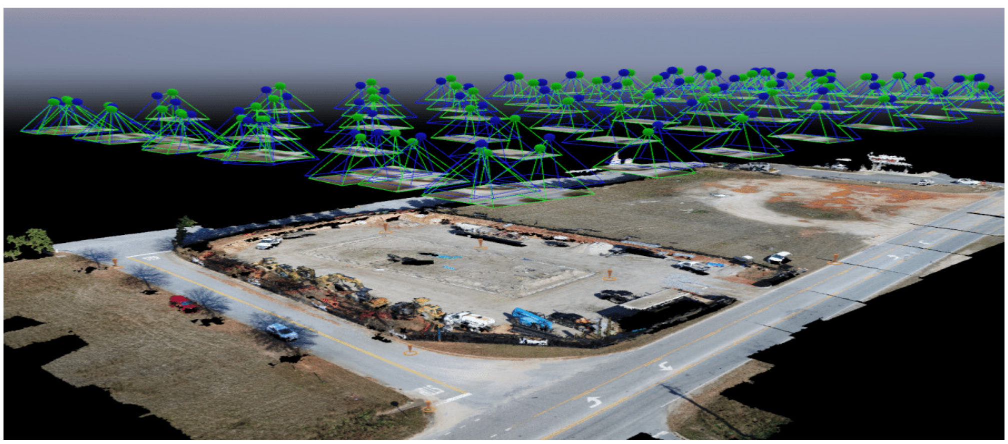

Figure 4: Markers placed on the ground

The process of 3D Mapping can be explained more clearly by the following flowchart:

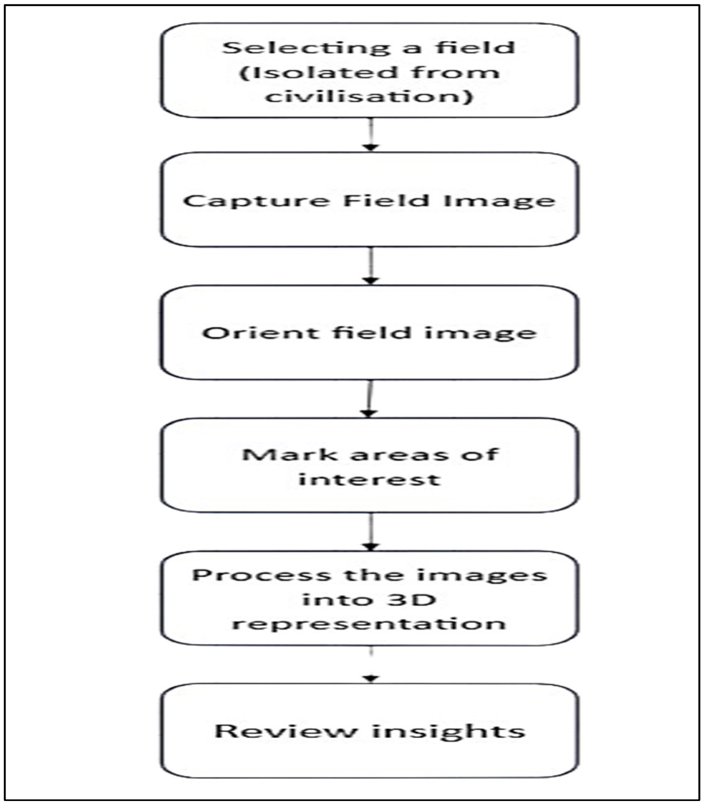

Figure 5: Flowchart of the 3D mapping process

Feature 2: This proposed framework for building a façade inspection with UAVs has three phases: coarse and precise registration and (Building Information Modeling) BIM-based image management. The GPS, IMU and optical parameters in UAV images are used to create virtual cameras in BIM, and BIM template images are generated for coarse registration. Precise registration is achieved using the GHT algorithm to extract building façade components. The UAV images are then projected onto the elevation view to generate an as-is orthophoto, aligned in both 2D and 3D views of the model.

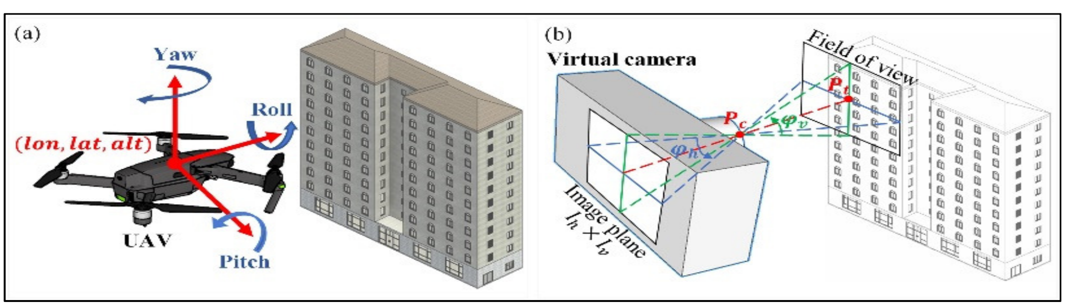

Figure 6: Shows the process of BIM carried out by the drone imaging

The following flowchart can more clearly explain the process of BIM-base imaging

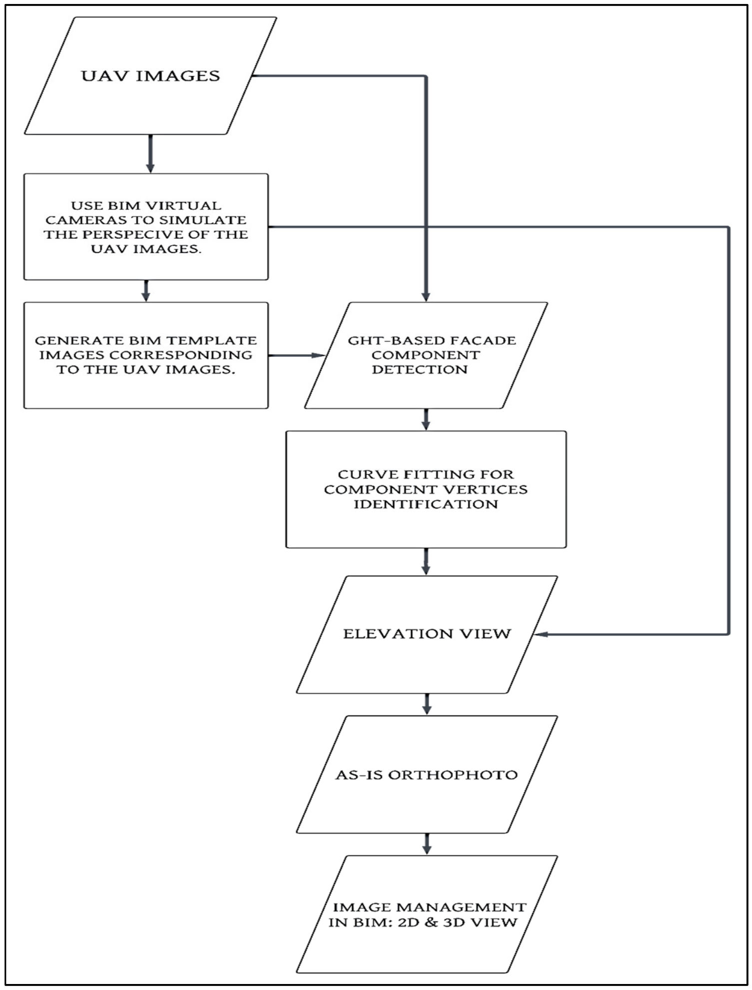

Figure 7: Flowchart of the BIM Process

We analyze data using **Tables 1** & **2** and perform additional calculations for accuracy.

Camera Calibration:

The camera calibration matrix K can be calculated as:

K = [[fx, 0, cx], [0, fy, cy], [0,0,1]],

Where,
fx and fy are the focal lengths in pixel units, and cx and cy are the principal point offsets.

Image to world coordinate transformation:

If Xw is a 3D World point and xi is its corresponding 2D image point, their relationship can be modelled as:

xi = K[R|t]Xw

Where,
R and t are the rotation matrix and translation vector from world coordinates to camera coordinates.

Point cloud generation:

Given a set of matched features between multiple drone images, the 3D position Xj of each point j can be estimated by triangulation:

$$\boxed{\mathbf{Xj} = \frac{(\mathrm{K}^{\wedge}-1*\mathrm{xi1})\ \mathrm{X}\ (\mathrm{K}^{\wedge}-1*\mathrm{xi2})}{||(\mathrm{K}^{\wedge}-1*\mathrm{xi1})||}}$$

Where, xi1 and xi2 are the corresponding image points in two views.

Digital elevation model:

The elevation Z at grid location (x,y) can be estimated as:

Z(x,y) = 1/n * Σ Zi Where, Zi is the elevation measurement from 3D point i, and n is the number of points within the grid cell at (x,y).

Volume Calculation:

The volume V of a region on the elevation model can be computed as:

V = Σ(Z(x,y) – Zref)ΔxΔy Where, Zref is a reference elevation, Δx and Δy are the grid resolutions, and the summation is over all cells in the region.

4. Conclusion

In conclusion, this research presents a reliable UAV-based 3D mapping method using photogrammetry and unveils exciting possibilities for the future. The ability to generate high-quality models in various landscapes and seamless integration with GIS platforms establishes a powerful tool for spatial analysis. This technology offers significant contributions to diverse fields, such as improved decision-making in urban planning, construction, and environmental monitoring and faster disaster response through 3D mapping of affected areas. Furthermore, using Raspberry Pi Camera Modules and smart devices within this framework offers a compelling combination of affordability, flexibility, and accessibility. UAVs' lightweight and manoeuvrable nature facilitates efficient data acquisition for accurate 3D modelling while integrating smart devices, which enables real-time data processing and analysis. However, further exploration is necessary to unlock the technology's full potential. By focusing on areas like autonomous UAV operations, advanced data processing with machine learning, and sensor integration, UAV-based 3D mapping has the potential to become a transformative technology across various disciplines. It can empower us to gather richer spatial data, make informed decisions, and ultimately, better manage the world around us.

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