Review of Drone Swarms Usage for 3D Reconstruction

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***Abstract*—Three-dimensional reconstruction has become an essential tool in many fields, including archaeology, architecture and civil engineering. The use of drone swarms for 3D reconstruction has gained momentum due to their ability to cover large territories, obtain high-resolution images and work in dangerous or remote places. However, the use of drone swarms for 3D reconstruction is also fraught with significant problems and limitations. One of the serious problems is the limited flight time of drones, which can affect the amount of data that can be obtained in one flight. In this article, we evaluate existing solutions and identify the main problems and limitations associated with drone swarms for 3D reconstruction. We also propose a solution concept for three-dimensional reconstruction using a centralized control drone swarm architecture, pre-planned trajectories and photogrammetric tools for building three-dimensional models.**

I. Introduction

In recent years, three-dimensional reconstruction process of buildings has become increasingly significant. This can be attributed to the expansion of urban areas and the growing need for accurate information regarding structures with diverse purposes. The reconstruction includes the creation of a precise and detailed model of the building, which can be utilized for various purposes, such as urban planning, facility management, and building inspection [1], [2].

However, the traditional methods of three-dimensional reconstruction are fraught with difficulties, as they require manual control and measurements, which can be both time-consuming and labor-intensive, and often lead to incomplete or inaccurate data. Nevertheless, the recent development of drone technology has significantly enhanced the three-dimensional reconstruction, making it faster, more accurate, and safer.

The use of drone swarms equipped with cameras and sensors allows for the collection of high-quality images and data from different perspectives, providing a detailed and accurate representation of the structure and layout of the building. Additionally, drones can access hard-to-reach areas, which may pose safety risks or lack accessibility, making data collection difficult or dangerous. Consequently, the use of unmanned aerial vehicle (UAV) technology has revolutionized the three-dimensional reconstruction of buildings.

A swarm of drones is a system of interacting agents designed to accomplish a specific task. The primary goal of the swarm is to use a system of simple agents instead of a complex agent, providing flexibility, reliability, and scalability. In the task of three-dimensional reconstruction, a swarm of drones has several advantages over a solution that uses a single drone. Firstly, drone can capture high-quality images and data from various angles, providing detailed and accurate information about the structure and layout of a building. Secondly, drones can explore hard-to-reach areas such as roofs, facades, or ground-level structures, where safety issues or lack of access may hinder or make data collection dangerous. Thirdly, a swarm of drones can distribute tasks among the drones, providing parallel processing and faster data collection.

The aim of this study is to analyze the using of drone swarm in 3D reconstruction task for developing the system concept that allows to perform the process of data collection and reconstruction adaptively. The main objectives of the study are:

1) To identify the main ideas of drone swarm control for 3D reconstruction tasks.
2) To investigate the existing methods using drone swarms.
3) To define the main problems of using a drone swarm in 3D reconstruction case of large objects.
4) To develop a solution concept for 3D reconstruction task using a swarm of drones.

The rest of the paper is organized as follows. Section II discusses the current state of the field. Sections III and IV provide a description of the literature review and selected papers. Sections V and VI contain a description of the comparison criteria and a comparative analysis of existing works. Section VII discusses the review and describes the concept of a possible solution. Section VIII contains the conclusion and summary of the study.

II. State of art

As research progresses, it's important to gain an in-depth understanding of the current state of the art in this field. In this section, delving into the architecture of swarm agents, the control methods utilized to coordinate these agents, and the various approaches that researchers have taken to build 3D models using drone swarms will be discussed.

A. Architectures of swarm agents

There are several architectures of drone swarms that can be used for 3D reconstruction of buildings using RGB images. Generally, these architectures involve coordinated flight of multiple drones to obtain overlapping images, which can be used to create a 3D model [3]. One approach involves using a leader-follower swarm, where the main drone leader is equipped with a high-resolution RGB camera and flies along a pre-planned trajectory over the target area, while a group of smaller drones (followers) fly in formation around the leader, capturing additional images from various angles. The images are then combined to create a complete 3D model.

Another approach involves using a fully autonomous swarm, where each drone is equipped with its own camera and is coordinated with others in real-time to avoid collisions and ensure adequate coverage of the target area. This approach requires more complex coordination algorithms and may be more computationally intensive, but it provides greater flexibility and adaptability in the data collection process.

B. Methods of control

When choosing methods for controlling a swarm of drones for three-dimensional building reconstruction, several methods can be considered [3], [4].

1) Centralized control: In this method, one central controller or ground station controls the movements of all drones in the swarm. The controller sends commands to the drones, such as their height, speed, and location, using radio signals or other communication systems. The advantage of this approach is that it provides precise drone coordination and is reliable in terms of maintaining accuracy in determining location.

2) Decentralized control: Unlike centralized control, decentralized control distributes control among individual drones in the swarm. In other words, each drone is responsible for autonomous navigation and decision-making about its movements based on its observations and communication with other drones in the swarm.

3) Hybrid control: This method combines aspects of centralized and decentralized control. Under this approach, the central controller may provide a general flight trajectory or waypoints for each agent, while drone itself uses sensors and other data to adjust its movements in real-time.

In general, the choice of control method depends on various factors, such as the size of the swarm, accuracy requirements, and the capabilities of the drones themselves. Software development also requires consideration of aspects such as collision avoidance and communication between drones, and battery discharge.

C. Approaches to building a 3D model

In recent years, there has been significant research into developing methods for constructing three-dimensional models based on RGB images. RGB input data refers to the photos captured by drone cameras and other sensor data, like GPS or odometry. The construction of a three-dimensional model can be achieved through various methods, including stereo reconstruction, structure from motion (SfM), multi-view stereo (MVS), and simultaneous localization and mapping (SLAM).

The construction of a three-dimensional model can be based on assumptions or a preliminary data, such as the shape of the object or its dimensions. However, in most cases, the model is constructed based on the features extracted from the input data. The process of constructing a three-dimensional model can be divided into several stages, including feature extraction, correspondence estimation, and surface reconstruction.

The quality of the constructed three-dimensional model depends not only on the accuracy of the input data but also on the algorithm used to construct the model. It is essential to evaluate the qualitative properties of the constructed model and approach, such as how to parameterize or change the model, estimate its accuracy, and treat any noise present in the final model. It is also important to consider whether the process can be configured or changed and to identify the most significant bottlenecks of such methods that may be important when working with them.

1) Structure from Motion: One of the popular methods of constructing a 3D model using RGB images obtained from monocular cameras is through Structure from Motion (SfM) techniques. SfM techniques rely on finding correspondences between features in multiple images and using them to estimate the 3D structure of the scene. Some popular SfM-based approaches for 3D reconstruction are VisualSfM [5], COLMAP [6], OpenMVG [7], and Bundler [8].

2) Multi-View Stereo: MVS involves using multiple images of a current scene from several viewpoints to compute a dense point cloud, which is then used to generate a 3D mesh. This technique is useful for generating highly detailed 3D models from a large number of images, but it can be sensitive to changes in lighting and requires significant computational resources. One popular MVS software is COLMAP [6].

3) SLAM: SLAM is a technique that allows a mobile robot or a camera to construct a map of an unknown environment while simultaneously keeping track of its own position within that environment. This technique has been adapted for 3D model construction, where the camera's movement and environment are mapped to produce a three-dimensional model. Researchers have proposed various SLAM algorithms for 3D modeling, such as ORB-SLAM [9], LSD-SLAM [10], and Semidirect Visual Odometry (SVO) [11].

III. Literature overview

A. Search Principles

In order to conduct a thorough search for scientific papers on the use of drone swarms for 3D reconstruction, a variety of search queries were used. These queries included terms such as "drone swarm", "RGB imagery" and "3D reconstruction". Search engines and academic databases were used, including Google Scholar, IEEE Xplore, and ScienceDirect. The search principles are refined in order to find scientific papers within the past five years that are published in international journals and that are directly relevant to the topic of using drone swarms for 3D reconstruction based on RGB images.

B. Filtering Criteria

After conducting the initial search for articles on the use of drone swarms for 3D reconstruction based on RGB images, we developed the following criteria to filter articles:

1) Relevance: In terms of relevance, articles were selected based on their potential to contribute to the understanding of drone swarm technology for 3D reconstruction. Specifically, we sought articles that discussed the use of drone swarms for 3D reconstruction based on RGB images, and that described specific applications or technologies in this field.

2) Quality: To assess the quality of the articles, a variety of factors were considered. We evaluated the methodology used in the articles to ensure its soundness, and assessed whether the results presented were robust and the conclusions supported by the data presented. Additionally, we considered the reliability of the findings and their potential impact on the field of 3D reconstruction.

3) Focus: The focus of the articles was also taken into account when filtering the search results. We sought articles that were specific to the research question and provided novel findings or innovative approaches to using drone swarms for 3D reconstruction. Articles that presented a general review of literature on the use of drones for 3D reconstruction but were not focused on the specific research question were excluded.

4) Reliability: Finally, we evaluated the reliability of the articles based on several factors. The Hirsch index of authors, the level of citation of the article, and the reputation of the journal or publisher were all taken into consideration. We prioritized articles written by authors who were considered experts in the field or had a proven track record of publishing high-quality research.

Initially, according to the described queries, about 50 articles were found, affecting the use of drones and the process of three-dimensional reconstruction. By applying these filtering criteria, 6 works were selected, discussed below.

IV. Existing solutions

A. Lundberg C. et al

The article [12] proposes a rapid 3D modeling system based on drone swarm. The article discusses two models of drone behavior that are fused in the decision-making process: hovering (swarming) and data collection. As part of the work, methods of swarm coordination using GPS coordinates and inertial navigation systems to determine the position and orientation of the drone, as well as using a ground control point (GCP), are proposed. Additionally, the drones have a neighbor agent info (NAI) which provides position of the other agents in the swarm. The authors use the VisualSFM algorithm to build three-dimensional models that merge the collected data by a parallel GPU (Graphics Processing Unit) computing.

B. Rakha T., Gorodetsky A.

The article [13] provides an overview of the use of drones in the field of energy audit using three-dimensional reconstruction, as well as conducts their research on the applicability of technologies. Since pre-planned non-overlapping trajectories are used for drone movement, the solution can be expanded to the use of multiple drones. Also the authors empirically found that the stripe pattern and the archimedic spiral are effective methods for drone path planning. Drones are equipped with cameras and infrared sensors, data from which is processed by photogrammetry software such as Pix4D [14], DroneDeploy, and Agisoft Photoscan [15].

C. Paula N. et al.

The article [16] introduces a modular solutions for controlling multiple drones, providing path planning and autonomous drone control capabilities. To use multiple drones, the research area is divided into several zones in which each drone moves independently, collecting data from a fixed height, moving along a strip trajectory. The specific tools of three-dimensional reconstruction are not described in the article, since the authors focused on creating a simple interface for controlling and planning the trajectory for multi drones.

D. An Q., Shen Y.

The authors [17] consider the use of several drones in the task of active reconstruction. The main purpose of the study is to propose a scheme for choosing the best camera configuration for data acquisition, which uses Next-Best-View approach [18], [19]. The configuration is a drone location and camera orientation.

Elliptical trajectories are used as the trajectories of drone movement in the work. The images collected by each drone are used to build a local three-dimensional sub-model using SfM and MVS algorithms, which are then integrated into the final model.

E. Aydın M. et al.

The article [20] describes the key components of a MVS-based 3D reconstruction system, including the agents, the communication protocols between agents, and the data fusion mechanism used to combine the output of the individual agents. The authors also present a taxonomy of MVS-based 3D reconstruction systems, based on the number and type of agents used. Finally, the authors provide several case studies demonstrating the effectiveness of MVS-based 3D reconstruction in various applications, including archaeological site reconstruction, indoor mapping, and outdoor terrain mapping.

F. OptiMaP

The article [21] proposes the swarm-powered Optimized 3D Mapping Pipeline (OptiMaP), that using edge computing and ad-hoc cloud paradigms come in support to keep the reconstruction stage locally. The authors describe the principles of the organization of drones and their movement by dividing the study area into sections with independent trajectories for each drone. The system optimizes workload generation and distribution by using Variable Neighborhood Search (VNS) [22] based heuristics, which solves the problem of coverage distribution for special swarm-based clouds (CAPsac) [23]. OpenDroneMap [24] toolkit is used to build three-dimensional models. The system is implemented as a collaborative embedded Robot Operating System (ROS) [25] application.

V. Comparison criteria

Now that we have conducted the primary search, it is necessary to compare and evaluate the selected solutions, we can group the criteria into the following categories:

A. Solution architecture

1) Organization of agents: Drone swarms can be organized into three categories: homogeneous, heterogeneous, or mixed.

- A homogeneous organization involves drones with the same capabilities and sensors.
- A heterogeneous organization comprises drones with varying capabilities and sensors.
- A mixed organizations have both homogeneous and heterogeneous drones.

2) Control of agents: The control of agents refers to how the drones are controlled during the operation. It can be centralized, decentralized, or hierarchical.

- In centralized control, a single device controls all drones.
- Decentralized control is where each drone is autonomous but can communicate with the other drones.
- Hierarchical control is where drones are grouped and controlled according to their capabilities.

3) Communication between agents: Communication between agents is essential to ensure proper operation.

- Direct communication means that all agents can communicate with each other.
- Nearest neighbor communication is where drones communicate with their immediate neighbors. The "neighborhood" can be defined by the central controller, for example, as the nearest drones or other drones in the field of view.
- Autonomous movement is where there is no communication between drones.

B. Level of autonomy

This criteria group refers to the degree of autonomy used in the drone swarm for 3D reconstruction based on RGB images. The most frequent degrees are:

- direct operator control (no autonomy)
- independent movement of drones along a given trajectory, for example, reported by a central controller under the supervision of the operator or without his participation
- autonomous movement in an unknown environment (full autonomy)

It could include features such as autonomous navigation and obstacle avoidance.

1) Considered object shape: An important factor to consider is the shape of the object under study. This refers to the shape and complexity of the object being captured by the drone swarm, as this can affect the flight path and data collection. Some drone solutions are restricted to certain shapes, while others can handle any shape.

2) Trajectory construction principles: This refers to whether a pre-planned trajectory is used by the drone swarm during flight. The trajectory can be built in advance before the start of the mission, or drones can move autonomously, generating a trajectory as they move in area. Because the trajectory is a common feature in many solutions, allowing for automatic movement without the need for operator intervention.

3) Trajectory shape: The shape of the flight path used by the drone swarm during data acquisition is also an important consideration. Drones may move in a zigzag, circle, or indefinite path.

C. Data

1) Collected data: The main type of data collected can be either RGB or RGB-D. RGB data is used to capture color images, while RGB-D data includes depth information.

2) Additional data: Additional data collected or used in the process includes GPS, IMU, and GCP. GPS provides location data, IMU measures acceleration and rotation, and GCP refers to ground control points used for accuracy assessment.

3) Preliminary data: This criteria refers to any preliminary data used to assist with the 3D reconstruction process. For example, solutions can use point clouds obtained with lidar as a map for planning and moving drones [26], [27].

D. 3D reconstruction

1) Image overlap: Image overlap is the percentage of image overlap used to create the 3D model.

2) Reconstruction tools: The tools used to obtain a three-dimensional model can vary, such as Structure from Motion (SfM), Multi-View Stereo (MVS), and Light Detection and Ranging (LIDAR).

E. Equipment

1) The number of agents: The number of agents used in the system, such as the number of drones, can affect the efficiency and accuracy of the operation.

2) Drones/cameras: The models of drones and cameras used in the operation can also vary, affecting the quality of data collected.

F. Accuracy

The measurement of accuracy is essential in assessing the quality of the 3D model created. So we need to take into account which methods of evaluating the constructed trajectories and three-dimensional models are used in reviewed works.

By considering each criterion, it is possible to determine which solution best fits the intended use case.

VI. Comparative analysis

A. Solution architecture

We determined that the most popular system architecture is centralized by comparing the solution architectures shown in Table I. Hybrid architecture implies the implementation of some calculations, for example, partial image processing

(*Lundberg C. et al*) or local map construction (*OptiMaP*) on agents in the presence of a ground computing center.

All solutions implement direct communication between agents, i.e. each drone has information about other drones, this is provided by the central node that maintains communication with all drones.

Most solutions use a heterogeneous organization of agents, i.e. drones perform the same tasks during the flight. Heterogeneous organization in *Lundberg C. et al* and *OptiMaP* implies the presence of one main drone (leader) and several less powerful drones (followers) following the leader and collecting additional information about the object.

TABLE I. COMPARISON OF SOLUTION ARCHITECTURES

	Agent	**System**	**Connection**
Lundberg C. et al	heterogeneous	hybrid	direct
Rakha T., Gorodetsky A.	homogeneous	centralized	direct
Paula N. et al	homogeneous	centralized	direct
An Q., Shen Y.	homogeneous	centralized	direct
Aydın M. et al.	heterogeneous	hybrid	direct
OptiMaP	homogeneous	hybrid	direct

B. Autonomy level

Comparing the level of autonomy of solutions, the results of the comparison are shown in Table II, we found that all solutions apply the approach of constructing the flight path of drones before the mission. In such cases, the mission does not require an operator to control the drones, which move along the planned trajectory due to the commands of the central node.

Most solutions do not use restrictions on object shape under observing, but limit the area under observing by specifying global coordinates, for example, using GPS.

The most used drone path shape is a strip path, but works *Lundberg C. et al* and *An Q., Shen Y.* note good results when flying along an elliptical or spiral trajectory.

TABLE II. COMPARISON OF SOLUTION AUTONOMY LEVEL

	Object shape	**Path shape**
Lundberg C. et al	-	spiral
Rakha T., Gorodetsky A.	cube	strip
Paula N. et al	-	strip
An Q., Shen Y.	cube	ellipse/sphere
Aydın M. et al.	-	strip
OptiMaP	-	not specified

C. Data

Table III describes the data used and collected. During path planning and mission execution, reviewed works do not use any additional input data about considered object, for example, point clouds obtained using ground LIDAR, except for the parameters of observing area.

Solutions used data from RGB cameras as collected information about object, except for *Rakha T., Gorodetsky A.* that also collects data from infrared sensors.

To increase the accuracy of the drone localization and further image processing, some solutions use GPS data, as well as data from the drone inertial system (*Rakha T., Gorodetsky A.*).

TABLE III. COMPARISON OF DATA USED IN SOLUTION

	Collected data	**Additional data**
Lundberg C. et al	RGB-images	GPS
Rakha T., Gorodetsky A.	RGB+infrared data	GPS+INS
Paula N. et al	RGB-images	GPS
An Q., Shen Y.	RGB-images	-
Aydın M. et al.	RGB-videos	-
OptiMaP	RGB-images	GPS

D. 3D reconstruction

Some works use image overlap at the level of 90%, with a recommended range of 60-80%, which increases the accuracy of the resulting model, but requires more images. However, most solutions do not explicitly specify the overlap percentage used. The most used approach for constructing three-dimensional models is SfM. Works *Paula N. et al* and *An Q., Shen Y.* focus on planning and controlling a swarm of drones, so the authors do not explicitly describe the process of constructing three-dimensional models.

The results of the comparison are presented in Table IV.

TABLE IV. COMPARISON OF SOLUTION RECONSTRUCTION

	Image overlap (%)	**Toolkit**
Lundberg C. et al	not specified	SfM
Rakha T., Gorodetsky A.	95	SfM
Paula N. et al	not specified	not specified
An Q., Shen Y.	not specified	not specified
Aydın M. et al.	not specified	SfM + MVS
OptiMaP	90	SfM

E. Equipment

Most of the work during the experiments used 3-4 drones. At the same time, *An Q., Shen Y.* and *Aydın M. et al.* describe a general approach, and *OptiMaP* uses simulation, so the authors do not provide descriptions of specific drone models.

The results of the comparison are presented in Table V.

TABLE V. COMPARISON OF SOLUTION EQUIPMENT

	Agent numbers	**Drone/camera models**
Lundberg C. et al	3	DJI S1000+/Parrot AR
Rakha T., Gorodetsky A.	N	DJI Inspire 1
Paula N. et al	3	DJI Flamewheel F550
An Q., Shen Y.	N	not specified
Aydın M. et al.	1-4	not specified
OptiMaP	5	simulation (not specified)

F. Accuracy

Most solutions do not evaluate the accuracy of the constructed model by comparing point clouds, because they do not have a priori data or an accurate model created, for example, using LIDAR technology. *Rakha T. Gorodetsky A.* and *Paula N. et al*, focusing on the construction of motion trajectories and drone control, compare the real trajectories of drones after a fliyng with those planned paths using way points. *An Q., Shen Y.* uses MSE trajectories of drones relative to ground truth.

VII. Results

At the moment, swarm drones with RGB cameras are used for three-dimensional reconstruction of buildings in several areas, such as construction, architecture and tourism [28].

A. Main problems and solutions

However, there are some problems and limitations that may make it difficult to use these solutions.

1) Limited range: Most swarm drones have a limited range, which can make it difficult to reconstruct large buildings in three dimensions. For example, if a swarm drone has a range of 1 kilometer, and it needs to reconstruct a very large building at a distance of 2 kilometers, then for these purposes it will require moving the drone or using a large number of swarm drones.

2) Limited autonomy: Due to the limitations of the autonomy of most drone models, they require constant monitoring, for example, during long flights, it may be necessary to charge the battery, which requires an operator.

3) Localization of camera: The instability of the drones may cause the camera position to shift, which may affect the accuracy of the three-dimensional reconstruction. For example, if the drone is at a height, even a small wind can shift its position, which can lead to errors during the reconstruction of the building.

Also, we need to remember the necessary flight zones permits for drone use, as well as possible violations of people's privacy [29]–[31].

Some of the limitations can be solved by using more expensive and powerful drones, this way we can

- extend the range and ensure reliable communication between the drones and the ground stations
- increase the autonomous flight time of the drones, prevent loss of control during prolonged operation

However, one of the advantages of drone swarms used is the low cost of agents, which allows to improve the quality and speed of work due to their number.

For solving the problem of localization of drones, stabilization systems can be used, which will be able to eliminate the drone instability and ensure the accuracy of the camera location [32]. It is also useful to apply additional navigation systems, such as GCP and GPS. This solution can help determine the exact location of the drone and camera, which will ensure high accuracy in three-dimensional reconstruction.

Other possible solutions for creating a solution for constructing three-dimensional reconstruction of buildings using swarm drones with RGB cameras may include:

- Creating or using a tracking and control system that allows us to study reconstruction data during construction, monitor drone operations, such as Pix4D or SkyCatch [33].
- Development of a parameterized system that allows us to upload data about the building and adjust the parameters of the construction
- Using a Machine Learning system to improve the accuracy and quality of reconstruction [34]–[36]

B. Solution concept

Let's consider the main components of the solution concept for three-dimensional reconstruction using swarm drones. Fig. 1 shows the scheme of the solution, which is described below.

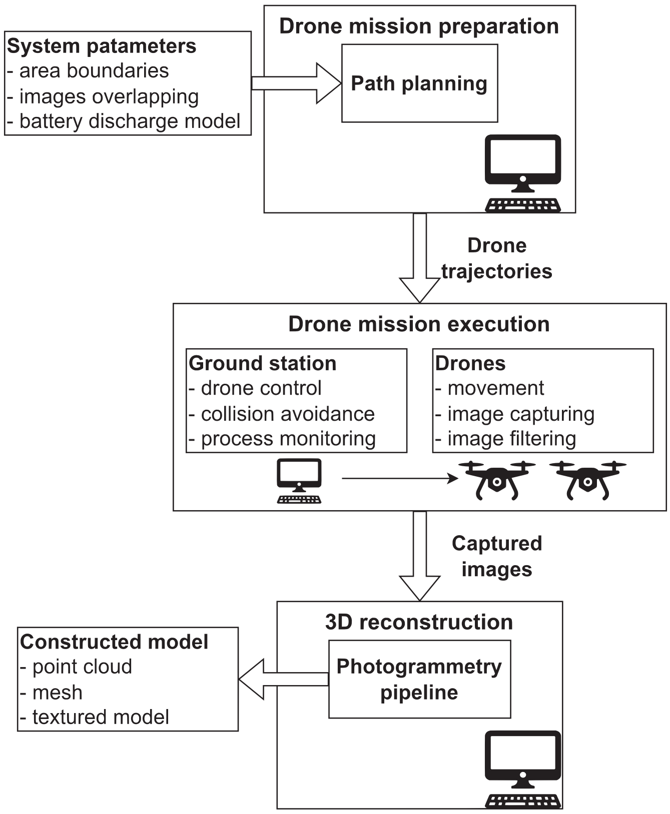

Fig. 1. Solution concept

1) Solution architecture: The most suitable organization of drones in a swarm is a centralized architecture that provides the following advantages

- Interaction of drones with each other and with a single central controller that can ensure effective communication and coordination between drones, reducing the risk of interference and collisions.
- Providing control and monitoring of the entire swarm, allowing to make adjustments and interventions in real

time, monitor the drone's battery life, its location and other important parameters, ensuring effective mission planning and execution to ensure maximum coverage and accuracy, allowing more accurate and comprehensive data to be obtained for further processing.
- The ability to increase or decrease the drone number used for three-dimensional reconstruction, depending on the size of the covered area, the required level of detail and available resources.
- A guarantee that drone fly within predetermined safety limits, avoid no-fly zones and follow certain flight patterns, reducing the risk of accidents and collisions with other objects or people.

2) Path planning and data collection: The flight path planning of drones should be carried out before the flight, as this can provide several advantages, such as:

- Consistency and repeatability: The flight path can ensure that every time a mission is repeated, all drones follow the same flight path. Such predictability can facilitate planning and decision-making and reduce the risk of unexpected results or errors, as well as facilitating comparison and analysis of different data sets.
- Optimized resource utilization: The flight path of the drone can optimize the use of battery resources by estimating the energy required to complete the entire mission and adjusting the flight path accordingly [37]. This way we can ensure that the drones have enough time for autonomous operation, and prevent them from discharging during flight, reducing the risk of data loss.
- Efficient data collection: The drone's flight path can provide efficient data collection, ensuring that the drones cover the entire area of interest with the required degree of detail and overlap, as well as explore the object at the right angles and in the right positions [38]. In this way, we will be able to minimize the amount of time and resources needed to collect data, reduce operating costs and increase efficiency.

Also, an important function is the assessment of the suitability of the collected RGB images for use in reconstruction. However, such selection was not applied in the works discussed in Section III. When capturing from drones, there is a high risk of obtaining a low-quality or inapplicable image. It is reasonable to carry out minimal filtering of photos on drones, since it does not require large computing resources, reduces the load on the communication network, and improves the quality of the final 3D model [39].

For three-dimensional reconstruction, we can apply photogrammetry, which has been used for several decades and has a well-proven set of methods and tools, which makes it easy to integrate it into existing workflows. This usually gives more accurate results than the MVS and SLAM algorithms, since it uses a larger number of images, while requiring minimal post-processing. The constructed models can be easily exported to various formats, for example, point clouds and textured meshes. In addition, photogrammetry is suitable for large-scale mapping projects, since it can be used to combine several images taken from different drones or ground cameras.

VIII. Conclusion

In conclusion, this study was aimed at analyzing the drone swarm usage in 3D reconstruction task for developing the system concept that performs the process of data collection and reconstruction. To achieve this goal, we have determined four tasks: identifying the main ideas of swarm drone control for three-dimensional reconstruction tasks, researching existing methods, defining problems of drone swarm usage in 3D reconstruction, and developing a solution architecture using swarm drones. During the literature review, we found several methods that can be used to determine the key components of the process, including drone control and three-dimensional reconstruction based on RGB images using GPS data to increase the accuracy of the three-dimensional model. We have also identified the basic ideas and principles of swarm drone management, such as path planning, autonomous flight and agent-based data processing, and defined the main problems of drone swarm usage in case of large objects. Finally, we proposed a concept for three-dimensional reconstruction using a swarm of drones, using a centralized architecture and a preliminary assessment of the degree of detail of the model.

Research shows that the use of drone swarms for 3D reconstruction opens up significant opportunities for various industries, including environmental monitoring. As further research, we consider the implementation of the solution concept, as well as conducting experiments to study the capabilities and characteristics of the resulting system.

References

[1] Y. Wei, V. Kasireddy, and B. Akinci, "3d imaging in construction and infrastructure management: Technological assessment and future research directions," in *Advanced Computing Strategies for Engineering: 25th EG-ICE International Workshop 2018, Lausanne, Switzerland, June 10-13, 2018, Proceedings, Part I 25*. Springer, 2018, pp. 37–60. [Online]. Available: https://doi.org/10.1007/978-3-319-91635-4_3

[2] G. Albeaino, M. Gheisari, and B. W. Franz, "A systematic review of unmanned aerial vehicle application areas and technologies in the aec domain." *J. Inf. Technol. Constr.*, vol. 24, no. Jul, pp. 381–405, 2019.

[3] C. Xu, K. Zhang, Y. Jiang, S. Niu, T. Yang, and H. Song, "Communication aware uav swarm surveillance based on hierarchical architecture," *Drones*, vol. 5, no. 2, p. 33, 2021.

[4] M. Abdelkader, S. Güler, H. Jaleel, and J. S. Shamma, "Aerial swarms: Recent applications and challenges," *Current robotics reports*, vol. 2, pp. 309–320, 2021.

[5] C. Wu, S. Agarwal, B. Curless, and S. M. Seitz, "Towards linear-time incremental structure from motion," *International journal of computer vision*, vol. 104, no. 2, pp. 286–300, 2013.

[6] J. L. Schönberger and E. Burnaev, "Sfm-toolkit: A structure-from-motion toolkit," 2016, software available at https://github.com/colmap/colmap. [Online]. Available: https://colmap.github.io/

[7] P. Moulon, P. Monasse, and R. Marlet, "Openmvg: A multiple view geometry library," *The International Journal of Computer Vision*, vol. 110, no. 3, pp. 223–252, 2014.

[8] N. Snavely, S. M. Seitz, and R. Szeliski, "Photo tourism: exploring photo collections in 3d," in *ACM Transactions on Graphics (TOG)*, vol. 25, no. 3. ACM, 2006, pp. 835–846.

[9] R. Mur-Artal, J. Montiel, and J. Tardós, "Orb-slam2: an open-source slam system for monocular, stereo, and rgb-d cameras," *IEEE Transactions on Robotics*, vol. 33, no. 5, pp. 1255–1262, 2015.

[10] J. Engel, T. Schöps, and D. Cremers, “Lsd-slam: Large-scale direct monocular slam,” in *European Conference on Computer Vision*. Springer, 2014, pp. 834–849.

[11] C. Forster, Z. Zhang, M. Gassner, M. Werlberger, and D. Scaramuzza, “Svo: Semidirect visual odometry for monocular and multicamera systems,” *IEEE Transactions on Robotics*, vol. 33, no. 2, pp. 249–265, 2016.

[12] C. L. Lundberg, H. E. Sevil, and A. Das, “A visualsfm based rapid 3-d modeling framework using swarm of uavs,” in *2018 International Conference on Unmanned Aircraft Systems (ICUAS)*. IEEE, 2018, pp. 22–29.

[13] T. Rakha and A. Gorodetsky, “Review of unmanned aerial system (uas) applications in the built environment: Towards automated building inspection procedures using drones,” *Automation in Construction*, vol. 93, pp. 252–264, 2018.

[14] B. Draeyer and C. Strecha, “White paper: How accurate are uav surveying methods,” *Pix4D White Paper*, 2014.

[15] L. Hinge, J. Gundorph, U. Ujang, S. Azri, F. Anton, and A. Abdul Rahman, “Comparative analysis of 3d photogrammetry modeling software packages for drones survey,” *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 42, pp. 95–100, 2019.

[16] N. Paula, B. Areias, A. B. Reis, and S. Sargento, “Multi-drone control with autonomous mission support,” in *2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. IEEE, 2019, pp. 918–923.

[17] Q. An and Y. Shen, “On the performance analysis of active visual 3d reconstruction in multi-agent networks,” in *2019 11th International Conference on Wireless Communications and Signal Processing (WCSP)*. IEEE, 2019, pp. 1–5.

[18] M. Mendoza, J. I. Vasquez-Gomez, H. Taud, L. E. Sucar, and C. Reta, “Supervised learning of the next-best-view for 3d object reconstruction,” *Pattern Recognition Letters*, vol. 133, pp. 224–231, 2020.

[19] G. Hardouin, J. Moras, F. Morbidi, J. Marzat, and E. M. Mouaddib, “Next-best-view planning for surface reconstruction of large-scale 3d environments with multiple uavs,” in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2020, pp. 1567–1574.

[20] M. Aydın, E. Bostancı, M. S. G¨uzel, and N. Kanwal, “Multiagent systems for 3d reconstruction applications,” *Multi Agent Syst. Strateg. Appl*, vol. 25, 2020.

[21] L. R. Costa, D. Aloise, L. G. Gianoli, and A. Lodi, “Optimap: swarm-powered optimized 3d mapping pipeline for emergency response operations,” in *2022 18th International Conference on Distributed Computing in Sensor Systems (DCOSS)*. IEEE, 2022, pp. 269–276.

[22] P. Hansen, N. Mladenović, J. Brimberg, and J. A. M. Pérez, *Variable neighborhood search*. Springer, 2019.

[23] L. R. Costa, D. Aloise, L. G. Gianoli, and A. Lodi, “The covering-assignment problem for swarm-powered ad hoc clouds: A distributed 3-d mapping usecase,” *IEEE Internet of Things Journal*, vol. 8, no. 9, pp. 7316–7332, 2020.

[24] O. Org, “Opendronemap: Open source toolkit for processing aerial drone imagery,” 2018.

[25] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, A. Y. Ng *et al.*, “Ros: an open-source robot operating system,” in *ICRA workshop on open source software*, vol. 3, no. 3.2. Kobe, Japan, 2009, p. 5.

[26] G. Bitelli, M. Dellapasqua, V. Girelli, S. Sbaraglia, and M. Tinia, “Historical photogrammetry and terrestrial laser scanning for the 3d virtual reconstruction of destroyed structures: a case study in italy,” *The international archives of the photogrammetry, remote sensing and spatial information sciences*, vol. 42, pp. 113–119, 2017.

[27] T. Luhmann, M. Chizhova, and D. Gorkovchuk, “Fusion of uav and terrestrial photogrammetry with laser scanning for 3d reconstruction of historic churches in georgia,” *Drones*, vol. 4, no. 3, p. 53, 2020.

[28] P. Sestras, S. Rosca, S. Bilasco, S. Nas, S. M. Buru, L. Kovacs, V. Spalević, and A. F. Sestras, “Feasibility assessments using unmanned aerial vehicle technology in heritage buildings: Rehabilitation-restoration, spatial analysis and tourism potential analysis,” *Sensors*, vol. 20, no. 7, p. 2054, 2020.

[29] S. Winkler, S. Zeadally, and K. Evans, “Privacy and civilian drone use: The need for further regulation,” *IEEE Security & Privacy*, vol. 16, no. 5, pp. 72–80, 2018.

[30] A. Fitwi, Y. Chen, and S. Zhu, “No peeking through my windows: Conserving privacy in personal drones,” in *2019 IEEE International Smart Cities Conference (ISC2)*. IEEE, 2019, pp. 199–204.

[31] J. R. Nelson, T. H. Grubesic, D. Wallace, and A. W. Chamberlain, “The view from above: A survey of the public’s perception of unmanned aerial vehicles and privacy,” *Journal of urban technology*, vol. 26, no. 1, pp. 83–105, 2019.

[32] D. Avola, L. Cinque, G. L. Foresti, R. Lanzino, M. R. Marini, A. Mecca, and F. Scarcello, “A novel transformer-based imu self-calibration approach through on-board rgb camera for uav flight stabilization,” *Sensors*, vol. 23, no. 5, p. 2655, 2023.

[33] Skycatch, “Skycatch—drones and data for industrial projects,” Website, 2021. [Online]. Available: https://www.skycatch.com/

[34] J. Chen, Z. Kira, and Y. K. Cho, “Deep learning approach to point cloud scene understanding for automated scan to 3d reconstruction,” *Journal of Computing in Civil Engineering*, vol. 33, no. 4, p. 04019027, 2019.

[35] E.-K. Stathopoulou and F. Remondino, “Semantic photogrammetry–boosting image-based 3d reconstruction with semantic labeling,” *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 42, pp. 685–690, 2019.

[36] D. Yu, S. Ji, J. Liu, and S. Wei, “Automatic 3d building reconstruction from multi-view aerial images with deep learning,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 171, pp. 155–170, 2021.

[37] D. Hong, S. Lee, Y. H. Cho, D. Baek, J. Kim, and N. Chang, “Energy-efficient online path planning of multiple drones using reinforcement learning,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 10, pp. 9725–9740, 2021.

[38] S. Mentasti and F. Pedersini, “Controlling the flight of a drone and its camera for 3d reconstruction of large objects,” *Sensors*, vol. 19, no. 10, p. 2333, 2019.

[39] M. Zaslavskiv, R. Shestopalov, A. Grebenshchikov, D. Korenev, and E. Shkvirya, “Method for automated data collection for 3d reconstruction,” in *2022 32nd Conference of Open Innovations Association (FRUCT)*. IEEE, 2022, pp. 308–315.