IR V1

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Abstract—This article is about discussing of the efficiency of formation of drone swarms in 3D scene reconstruction [1]. We consider that a formation is efficient where it gives a faithful reconstruction of the wanted object or scene. We can also consider that a formation is efficient when the reconstruction is obtained quickly or with a high definition of the wanted object/scene. This paper investigates how drone formations are tested and what results the original writers got from these experiments. We will also discuss about what has been done since the article has been posted and what they could have done to improve the quality of their results.

Article: Impact of drone swarm formations in 3D scene reconstruction

1 Introduction

Drones are increasingly being used in a lot of domains. From a military usage at the beginning [2], by using them as a remote weapons, to a humanitarian use [3] to search and rescue people after disasters or to bring unreachable resources. Whether it's for surveillance operation, bringing resources or an offensive use, a single drone unit tends to be expensive if we want to make it viable and robust. Furthermore the coverage of a large area (in a surveillance operation to rescue people after a disaster, for example) with only one drone, it tends to be too slow with the emergency of the situation. So, usage of swarms of tinier and lower cost drones appears.

Advantages of a drone swarm are the reduced cost as mentioned, and its robustness, if one drone broke down, the swarm can continue its mission whereas for a single drone it is the end of the mission. But another advantage, is the time spent on a surveillance because we can split our drones to cover more field in less time, and this is crucial for rescue operations. On the other hand, the use of low cost drones makes their autonomy drop, because of less powerful batteries, and the quality of their camera is reduced too.

In the following paper, we analyze an article [1] about the impact of the formation of a drone swarm on the accuracy of the 3D reconstruction. The section 2 overviews some related works in literature while section 3 presents contributions and results brought in the presented article. Section 4 discusses the limitation and positive points of the article. Finally, section 6, conclude our analysis.

2 Context and Related Work

Since 1979, UAV are used for photogrammetry because it's a low cost way to have photos from above, but it still needs some adjustments about the stability and it become more common around 2004 [4] and usage of 3D vision with small autonomous drones tends to be investigated [5]. With a swarm of autonomous drones, we can get a 3D reconstruction by taking multiple images with different angles of view. The algorithm SFM (Structure From Motion) which is used by the author of this article [1], uses this principle.

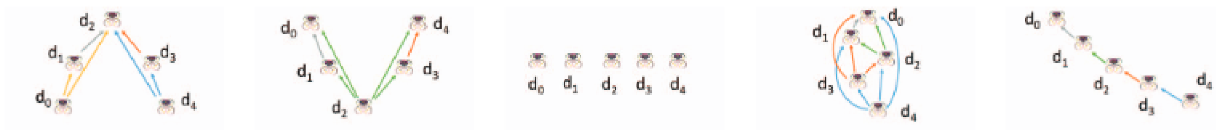
From 2001 [6], researches are made on how to keep a formation of mobile autonomous robots still. The aim is to make a "swarm" of robots move, from a point A to a point B, in an environment filled with obstacles and how it could avoid theses obstacles to reach their final destination without breaking their formation. These robots are not flying drones yet, but this is a first step forward the formation we will discuss.

Few years later, in 2006 [7], further researches are made about leading a swarm of UAV through a defined sequence of waypoints (in a 3D environment), in constrained environments. They found an algorithm to make the flight formation safe[1] in constrained spaces.

Then some researches has been focused on the dynamic adaptation of drone swarm to their environment to monitor in narrow spaces [8], they are searching a way to face the issue of holding a constant distance between drones in a formation. To do so, they put sensors on each drone and thanks to an algorithm, they dynamically adjust the position of each drone, according to the distance they calculate from other drones, without any external assistance.

And the last few years before this article [1], investigations were focused on optimizing drones trajectory to maximize the reconstruction accuracy. In 2014 study have been made on how efficiently encloses a target with a swarm of drones by adopting a geometric formation [9]. Furthermore, the usage of drone swarm for 3d reconstruction is under investigation since 2012 with the SFLy[2] project [10], which aims to create a swarm of autonomous drones to map an unknown environment. But there is no studies comparing the accuracy of the 3d reconstruction from several drone formations, and this is what the article [1] is about.

1. By "safe" they mean that drones inside the formation are not going to be damaged
2. Swarm of Micro Flying Objects



	d_0	d_1	d_2	d_3	d_4
d_0	0	1	1	0	0
d_1	0	0	1	0	0
d_2	0	0	0	0	0
d_3	0	0	1	0	0
d_4	0	0	1	1	0

Formation 1

	d_0	d_1	d_2	d_3	d_4
d_0	0	0	0	0	0
d_1	1	0	0	0	0
d_2	1	1	0	1	1
d_3	0	0	0	0	1
d_4	0	0	0	0	0

Formation 2

	d_0	d_1	d_2	d_3	d_4
d_0	0	0	0	0	0
d_1	0	0	0	0	0
d_2	0	0	0	0	0
d_3	0	0	0	0	0
d_4	0	0	0	0	0

Formation 3

	d_0	d_1	d_2	d_3	d_4
d_0	0	0	0	0	0
d_1	1	0	0	0	0
d_2	1	1	0	0	0
d_3	1	1	1	0	0
d_4	1	1	1	1	0

Formation 4

	d_0	d_1	d_2	d_3	d_4
d_0	0	0	0	0	0
d_1	1	0	0	0	0
d_2	0	1	0	0	0
d_3	0	0	1	0	0
d_4	0	0	0	1	0

Formation 5

Fig. 1: Drone formations with their graph matrices representing if a drone lies within the FOV of another one (from [1])

3 Contributions

3.1 Approach

The core of their contribution is the comparison of the localization and the reconstruction accuracy of a 3D scene by different drone formations. They compare five formations of five drones each (see figure 1). At a given time, each drone acquires an image and then compute a set of descriptors of this image before sending it to a reconstruction unit. Once that is done, a standard SFM[3] algorithm computes an estimation of the 3D coordinates of each point from the scene.

SFM principle is to match correspondences between the views, these points, which belongs to multiple views, are related thanks to a SIFT[4] descriptor. Then they refine this result with a bundle adjustments, which is an optimal estimation of the 3D coordinates of points of the scene and the camera's positions and calibrations simultaneously [11]. An optimal estimation aims to minimize errors between the projection on the estimated points of the scene and the detected points.

Sometime drones lies within the FOV[5] of other drones, making an occlusion of the scene which reduce the accuracy of its capture. But they decided to use this as side information (called CIV[6]) to calibrate cameras and improve the SFM accuracy by adding the camera in-view information (like its position and calibration) in the bundle adjustments. To use CIV, each drone needs to know the appearance of other drones, so at the beginning of the flight each drone communicates its appearance to the others with a SIFT descriptor. Furthermore, to foster CIV, drones in the back of the formation are set at a higher altitude (see the video sequence [12]).

All their tests are done within a simulation of a street with buildings, cars and street light (see figure 2).

3. **Structure from motion:** Estimation of a 3D object from capture of 2D images of the same object with different points of view

4. **Scale-Invariant Feature Transform :** Description of points of interest, that are invariant within the luminosity or the rotation

5. Field Of View

6. Camera In-view

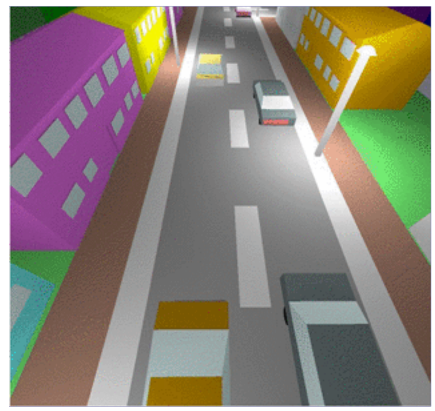


Fig. 2: Simulation (from [1])

3.2 Results

The first thing shown in their results is about drone identification, and they found that we need to match with at least 60% of their descriptors.

They have also shown that the more they exist matching points, belonging to the scene, between couples of different images and more the reconstruction will give better 3D point coordinates of the scene. To maximize matching points, we need to minimize the distance between them to get matching points, but in a configuration that minimize drone occlusions. The authors also precise that there is a correlation between σ and the improvement brought by the camera in view strategy. We can calculate σ with the following formula.

$$\sigma = \sum_{i=0}^{n} \frac{|S_i|}{n} \tag{1}$$

Where n is the number of drones and $|S_i|$ is the number of drones the i^{th} drone has in his field of view.

Next, they compare each drone formation on an accuracy criteria. And for each formation, they look the average MSE[7] between what they expect and what they actually got with the simulations. Results show that the first formation (see Fig.1) is the formation which got the lower average MSE thanks to the minimum number of occlusions and the different distances of the UAVs with respect to the scene to be

7. Mean Squared Error

reconstructed. Still according to their results, the formation one has the highest value of σ, which correspond with the fact that σ helps for the accuracy of the reconstruction.

4 Discussion

4.1 Limitations

Given that this article is written for a conference (the 2016 IEEE International Conference on Image Processing), there is a certain amount of information lacking[8]. For the drone formations, there is no further information on the height of each drone from the scene, or even the distance there is between each of them. In the *Experimental results* section of the article, there is an *Avg. baseline* value for each formation, but there is no clue on what unit is used there, making the result harder to interpret. The fact that this value is also a mean of the distance between drones is not either useful.

There is also other absent information that would have been useful if we want to reproduce the experiment, like information about the experimental conditions. What program they used to realize their environment and which parameters. Further information would have been good to have like camera characteristics, or even drone ones, like length, width, speed etc...

Now we are going to talk about improvements they could have done to their experiments. The simulation could be more realistic in terms of scene graphics, because in the given image we saw building made of simple shape and unified colors, and they also could add moving objects to the scene (despite there is cars on the images, we can see in the video [12] that they are not moving).

Their contributions are about comparing drone formations and it would make sense to use more or less drones in each formation and why not comparing results from formations with different number of drones (e.g. comparing a five drone formation with a six drone formation) especially as they use a simulation it would be easy to setup, but they said that they would test the scalability of their result in an future research.

Finally, they just compare the accuracy of the 3d reconstruction, but one of the reasons to use a drone swarm is the time of the reconstruction, so it would be more interesting to add a comparison of the speed of the reconstruction from each formation to see if formations have an impact on it too. But they also said that it would be tested in a future work.

5 Positive points

The fact that the experiment is realized in a simulation allow them to have a deterministic model, which guarantee that each formation has the same scene to analyze, making the comparison possible. That being said, they also tried to make the experiment more realistic by adding some noise to camera location, which is inherent to real world sensors.

8. We didn't find (or there is not?) a more detailed version of this article.

6 Conclusion

We saw in the discussion part (Sec. 4), that drone swarm formation plays an important role for the quality of the reconstruction of a scene. In the article [1] they mainly speaks about the precision of the reconstruction over the other parameters (like the speed of the reconstruction). After comparing five formations of five drones each, they found that an inverted **V** shaped formation gives a better reconstruction accuracy than the others. The experimental conditions are not really perfect, they could have used a better 3D engine, compare more formations with different amount of drones in it, but in fact they are the first to do such experiences, furthermore, they said that there will be more experiences about this subject. Up to now, there is no other article done, which aims to compare drone formations, not even from the same authors. A possible way to improve their results may lie in using other methods than the bundle adjustment which is a highly ”expensive” algorithm. The method discussed in the article [13] could be a path to explore for in order to obtain better, or faster results.

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