UAV path planning for photogrammetric capture of buildings towards disaster scenarios

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Abstract: At the scene of an emergency, first responders operate in a complex environment with limited knowledge about hazardous areas. This lack of insight is a hindrance to effective intervention. Utilizing Unmanned Aerial Vehicles (UAVs) for generating scans of the environment is one possibility to receive rapid and accurate information about hazardous conditions. Although many fields adopt UAV remote sensing, their efficient application poses a variety of research problems. Optimization of path planning for sufficient data capturing that allows 3D reconstruction is one of these problems. This paper concentrates on developing a path planning module that allows scanning the outside of the polygonal-shaped building site, considering a set of parameters, and inspecting existing strategies for outdoor UAVs. The generated module produces a path using the Traveling Salesman Problem based on the given UAV and 3D building model.

Keywords: UAV, BIM, Path Planning, Traveling Salesman Problem

1 Introduction

At a scene of an emergency, first responders often have to operate in dangerous and chaotic environments. Lack of insight into disaster scenes interferes with effective intervention. Examining the scene of an emergency with an Unmanned Aerial Vehicle (UAV) and notifying the first responders of the hazardous conditions in the operating environment allows to overcome possible overview deficiencies and respond to the hazard more rapidly and targeted. The utilization of UAVs has been widely adopted in many fields requiring remote sensing as a fundamental tool for surveying and mapping hard-to-reach locations [1]. Images captured by UAVs serve for reconstructing a point cloud, from which it is possible to generate a high-quality 3D model of the mapped area.

An efficient building examination with remote sensing is an important research problem. Many researchers focus on examining optimal scans by planning accurate paths before executing the UAV-scanning process. Inspecting optimal flight and sensor parameters and existing path planning strategies for outdoor UAVs in the literature is the first step of this study. This literature research defines the basis for setting parameters for the path planning solution of this study with the aim to implement a path planning module for a given outdoor UAV and a 3D building model. Setting the optimal parameters can be challenging, and multiple adjustments may be needed to obtain an accurate reconstruction efficiently. Some parameters to be considered in path planning for photogrammetric reconstruction are the selection of flight altitude, flying speed, image overlap, and camera parameters, particularly spatial resolution and focal length [2]. Investigating path planning strategies in literature was conducted to support the project goal - scanning the outside of the building from above and side. The method was developed for Building Information Modeling (BIM) models in Industry Foundation Classes (IFC) format, which represents a future standard format and methodology for built environments. The tool was implemented in python and tested using a sample UAV and sample BIM-building from the TUM campus in Munich.

2 State of the Art

UAVs have become powerful remote sensing tools for investigating hard-to-reach and dangerous locations because of the flexibility, cost-efficiency, and enabled controlled flight repeatability due to improving autopilots [2]. Although widely adopted in many fields, the efficient application of UAVs is of central interest for much recent research. Planning a convenient path that considers flight efficiency remains an open research question. Utilizing a BIM model as a simulation environment helps to design a path as the model geometry of the examined building allows a collision-free flight preparation while also evaluating the visual coverage and flight safety before execution [3]. Overall, two primary difficulties regarding path planning for UAVs can be defined: setting the optimal flight and sensor parameters and choosing the algorithm for the particular mission.

A critical open question regarding setting optimal parametrization is how to define the parameters best to achieve an optimization goal. Much recent literature focuses on parameters such as altitude, image overlap, and sensor resolution for UAV-based remote sensing. For instance, Seifert et al. [4] focus on adjusting parameters to impact the generation of good quality point clouds. The study concentrates on the influence of flight and sensor parameters on the flight time, the reconstruction details and precision, and the data processing duration. A trade-off occurs between quality and processing time. The study shows that flight time is linearly related to flight height. The lower the altitude, the higher the spatial resolution for more precise 3D reconstruction, but the longer the flight time [4]. Several researchers performing urban studies suggest a 10m distance between the UAV and building from both the ground and the façade [5], [6]. Optimal data collection is also strongly affected by the photographic overlap. Maximizing forward overlap increases accuracy but results in an exponential increase in processing time and has a negative impact on flight duration [4]. However, several researchers do not recommend reducing the overlap because it positively impacts the precision and leads to significantly lower error. Several studies conclude that a fixed forward overlap above 90% yields the best reconstruction detail and accuracy [1], [4]. Few researchers have addressed a precise parametrization of camera angle and flight speed. The angle of view describes the capture of multiple objects from the camera sensor and the determination of their distance [7]. For precise reconstruction, the captured area must be scanned from multiple angles while also considering the Field of View (FOV). Flight speed is highly influenced by the model of the UAV itself.

Finding an optimal path in a 3D model is a challenge widely addressed in the literature. An important question is defining a convenient path for a particular goal. This problem can be solved in many ways, denoted by the number of waypoints, their coordinates, and the camera orientation [3]. The literature offers a palette of examples for solving UAV path planning - from the artificial potential field to the commonly used graph search methods such as the Dijkstra and A* algorithm. A drawback of graph-based approaches is that they are time-consuming in complex environments and are prone to get trapped in the local optimum and never reach the global one [3]. Therefore, probabilistic methods such as Simulated Annealing (SA), genetic algorithms, and ant colony optimization are considered a less expensive alternative. Some literature sources interpret the UAV path planning challenge as a Traveling Salesman Problem (TSP). The fundamental characteristic of the TSP is the creation of a sequence for visiting a given list of places with the shortest distance possible [8]. For UAV path planning, the objective of the TSP is to plan a path that allows the UAV to visit all waypoints needed for scanning the object. The method for the study is developed utilizing TSP with the A* algorithm to find a path for a list of visited waypoints for scanning a building.

3 Methodology

The following chapter presents the main concept. The goal is the generation of a path planning module for outdoor UAVs that allows scanning of built environments efficiently. Figure 1 illustrates the workflow of the presented tool.

Figure 1: Workflow overview.

The first step of the method considers transforming the given BIM model in IFC format (Figure 2) to a voxel-based representation of the building (Figure 3). Calculating the bounding box from the IFC file allows obtaining an overview of the building measurements in meters for a precise voxelized representation. Therefore, a one-meter-sized voxelized model is created using the external software binvox mesh voxelizer by Patrick Min [9]. The created voxel-based data is structured in an octree, recursively subdivided into eight equal cubes until reaching the minimum voxel size. Figure 4 displays the grid resulting from a level of the octree. Each level provides different precision. A deeper level yields a more detailed vision of the building. The lowest level chosen in this study presents the voxelization of one-meter-sized cubes.

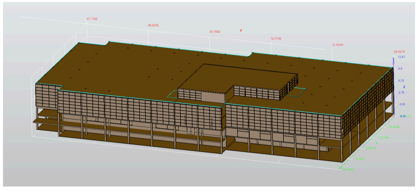

Figure 2: BIM input

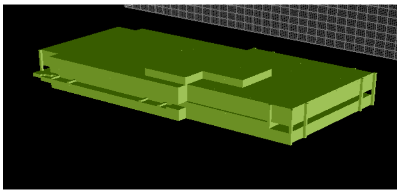

Figure 3: Voxelized model

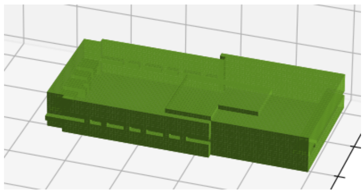

Figure 4: Octree representation

In the simplification step, the inside inaccessible voxels of the building are filtered out since they are irrelevant for outside path planning. The filling process is conducted using the flood fill algorithm. The algorithm is used to display the connected area around a given node in a multidimensional array. The flood fill algorithm allows defining the accessible voxels that can be used as waypoints in path planning by marking the outside empty voxels with the same value. Reversing the results switches the values inside and outside, meaning all inside voxels become flood-filled, which considers built environments consisting of more than one building. In the next step, a boundary box for path preparation is initialized by space extension. A building dilatation is used to guarantee a minimum distance around the building by extending the filled area with one voxel in all directions.

The simplified model is used as a basis for producing waypoints. Waypoints contain the coordinates to be visited by the UAV for scanning the building and the direction facing the building. Selecting a distance from the building aims to provide scans efficiently while considering collision avoidance. A defined maximum distance between two neighboring waypoints ensures an overlap between the two images. The distance between two waypoints is calculated using an equation that incorporates the overlap, the desired distance from waypoint to object, and the camera field of view:

$$\text{distance} = (\tan\left(\frac{\alpha}{2}\right) * \text{distance}) * 2 * \left(1 - \frac{\text{overlap}}{100}\right) \tag{1}$$

The waypoint-setting algorithm starts at a given position by collecting the coordinates of the voxels surrounding the particular node. It then iterates over the list of neighboring points until finding any neighbor on the building surface, meaning an occupied voxel at the neighbor position. The function calculates the optimal rotation matrix with the Kabsch algorithm [10] multiplied by the selected distance to align a vector between the current node and the neighbor. The coordinates of the newly created waypoint are calculated by summing up the resulting rotation matrix with the coordinates of the neighbor. A waypoint detected on the edge of the building is calculated by completely rotating over a corresponding axis using Euler angles. The waypoints are refined in the last step of the algorithm to filter the waypoints created in the direct vicinity of each other or in an inaccessible location as a consequence of the rotation process.

The TSP is a problem in combinatorial optimization, which describes the search for the most efficient path connecting a given number of cities by minimizing the cost of travel or the distance in-between. Solutions to the Traveling Salesman Problem can also be applied to the waypoint-connection problem underlying this study. The TSP is implemented with an A* algorithm to find the next nearest neighbor.

The study proposes three approaches. In the first approach, the waypoints are divided into clusters, and the TSP is performed between all elements in two neighboring clusters. The second approach takes an initial point and sorts the rest of the waypoints by distance away from it in ascending order. The closest n-points to the initial point are selected, and the TSP is performed on them to find the nearest neighbor. The last TSP is used with the cheapest insertion implementation - the algorithm places the next node in the position resulting in the cheapest possible costs.

Finally, the method performance is evaluated by assessing the coverage of the building and comparing the path planning strategies. A maximum depth distance is proposed to ensure a more accurate coverage analysis. The parameter aims to filter the visibly occupied voxels that are too far from the camera by calculating the Euclidean distance from the waypoint to the coordinates of surface points. The three presented methods regarding the TSP are analyzed by comparing the length, computational time, and path tendencies. The path length is calculated using the formula L = costs + len(waypoints), where the costs resulting from the TSP are summed up with the number of created waypoints.

4 Results

The study is tested on the BIM model of Technical University Munich Mensa. The resulting waypoints created with the tool are illustrated in Figure 5. The parameters are set to distance between the building and each waypoint of 12m, overlap of 20%, and a maximum depth distance of 20m. The coverage analysis results in a score of 85%, displayed in Figure 6. The uncovered area of the building surface is marked with red points. One limitation of the module occurs in this example. Details captured with a 20-meter-set maximum depth distance present an obstacle, as the distance from the building is fixed. One way to overcome the problem in the future is by featuring a flexible distance between the waypoints and the building.

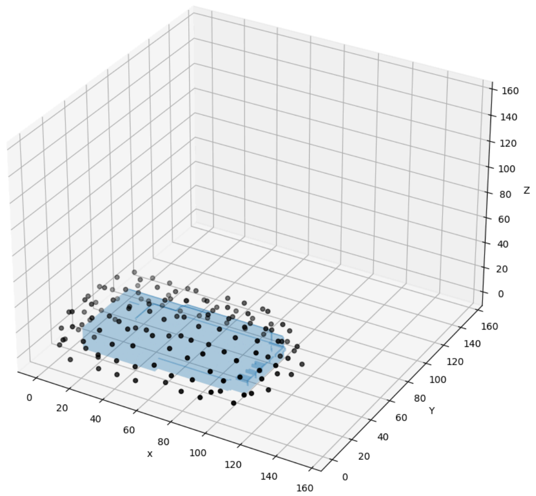

Figure 5: Waypoints with overlap 20% and distance 12 m

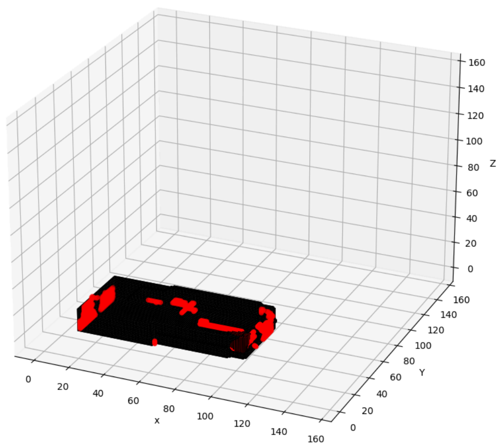

Figure 6: Coverage in black versus unseen points in red

The path planning analysis consists of the comparison of the three approaches considering TSP performed on the waypoints set. The analysis includes the processing time, the costs of the path, and the L-function, defined in Section 3. Table 1 summarizes the results of the path planning for the waypoint set selected in Figure 5. The path tendencies are visualized in Figures 7 - 9.

Table 1: Comparison of the three approaches

TSP	Number of waypoints	Processing time (s)	Costs	L
Clusters	141	106.68	2642.2	2783,5
Closest points	141	88.6	1320.9	1461.9
Cheapest insertion	141	902.8	1178.1	1319.1

The first approach is twice more expensive as the second and the last strategies and features the most randomness in the path, while the second and the third techniques have a more strict pattern yet are not perfectly aligned. The possible production of a more random path is a drawback of the discrete grid because each movement to the next point is equally expensive. Implementing a priority to one axis allows influencing a moving direction by making the cost cheaper along the particular axis. The feature helps prioritize moving along the chosen axis by equal distanced points. The study prioritizes the z-axis and x-axis. Without the priority, the first cheapest waypoint is considered a successor. This approach helps create a more consistent path, as demonstrated in the second and third approaches. The second approach has a significantly shorter processing time than the other two strategies. The cheapest costs are achieved utilizing the third approach. In the case of capturing buildings in disaster scenes, the second approach is the best because the path is produced in the shortest time. However, even this strategy should be speeded up regarding computational time in the future to provide quick results in time-pressing disaster scenarios.

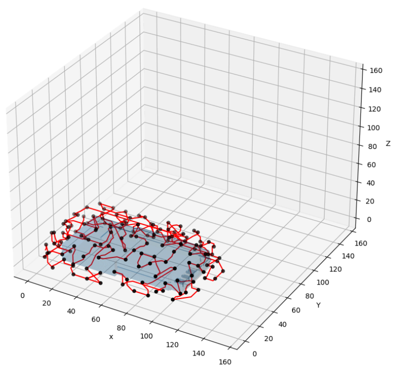

Figure 7: TSP with clusters

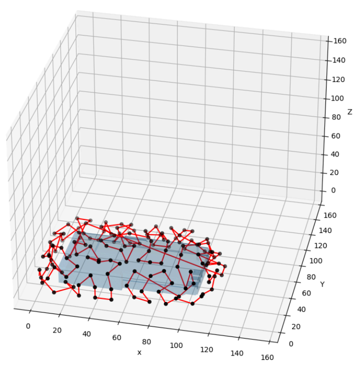

Figure 8: TSP on closest points

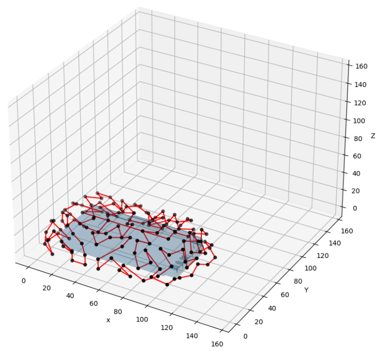

Figure 9: TSP with the cheapest insertion

Figure 10 describes the impact of the different overlaps and distances away from the building coverage. In Figure 11 logarithmic computational time is illustrated with chosen maximum depth distance of 20m and the focal length of 50mm. An overlap between 10 and 90% and a distance between 6 and 14m are the input for the analysis. A high coverage above 95% is achieved by waypoints close to the building with the highest overlap possible. Keeping the distance short and decreasing the overlap results in a slight decrease in the gained coverage. The plot is monotonically decreasing, meaning waypoints further away from the building and lower overlap produce a lower coverage percentage. The coverage decrease is also dependent on the specified maximum depth distance. The computational time is monotonically increasing. However, a set of waypoints far from the building with a high percentage of overlap produces a sharp increase.

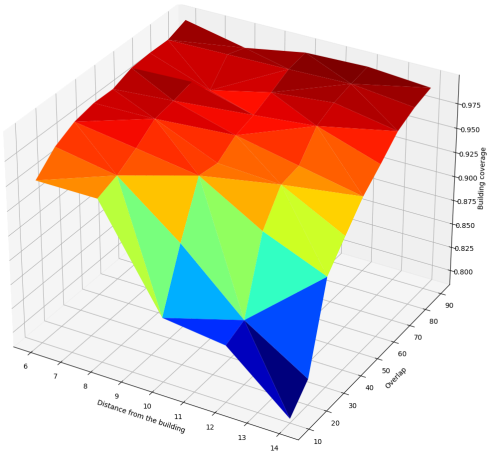

Figure 10: Gained Coverage

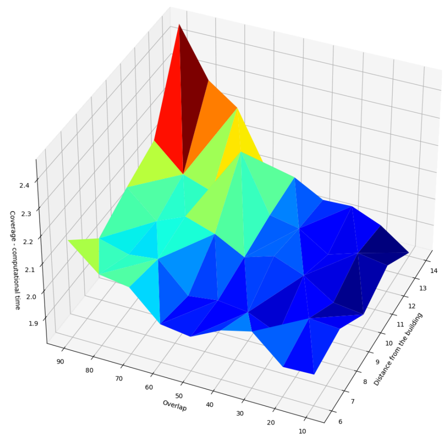

Figure 11: Computational time

5 Conclusion and Outlook

The main goal of this study was to develop a method for outdoor path planning for BIM models in IFC format, which allows for optimal scan acquisition in disaster scenarios. In the first step of the method, the input in IFC format was converted to a format that can be used for path planning. A voxel-based model was proposed, structured in an octree, and simplified with flood filled algorithm. As a next step, waypoint coordinates were defined, needed for the path planning algorithm based on the TSP with A* algorithm. The output is a resulting path consisting of a list of waypoints stored as coordinates in a JSON file. The method was tested and evaluated based on waypoints coverage and efficiency of path planning.

Based on the limitations of the developed method, a possible future work will be accelerating the path planning to adapt the module efficiently to the needs of first responders. The tool has to be adjusted concerning computational time to become applicable for disaster scenarios. One can implement a feature for distance flexibility since the fixed one is a limitation for buildings with indoor yards. Prioritization can be featured based on the current moving direction of the UAV instead of the axis.

Acknowledgements

The presented research was conducted in the frame of the project "Intelligent Toolkit for Reconnaissance and assessmEnt in Perilous Incidents (INTREPID)" funded by the EU's research and innovation funding programme Horizon 2020 under Grant agreement ID: 883345.

References

[1] D. Domingo, H. O. Ørka, E. Næsset, D. Kachamba, and T. Gobakken, "Effects of uav image resolution, camera type, and image overlap on accuracy of biomass predictions in a tropical woodland", *Remote Sensing*, vol. 11, no. 8, p. 948, 2019.

[2] L. Tang and G. Shao, "Drone remote sensing for forestry research and practices", *Journal of Forestry Research*, vol. 26, no. 4, pp. 791–797, 2015.

[3] A. Ibrahim and M. Golparvar-Fard, "4d bim based optimal flight planning for construction monitoring applications using camera-equipped uavs", in *Computing in Civil Engineering 2019: Data, Sensing, and Analytics*, American Society of Civil Engineers Reston, VA, 2019, pp. 217–224.

[4] E. Seifert, S. Seifert, H. Vogt, *et al.*, "Influence of drone altitude, image overlap, and optical sensor resolution on multi-view reconstruction of forest images", *Remote sensing*, vol. 11, no. 10, p. 1252, 2019.

[5] D. Roca, J. Armesto, S. Lagüela, and L. Díaz-Vilariño, "Lidar-equipped uav for building information modelling.", *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*, vol. 45, 2014.

[6] K. Themistocleous, A. Agapiou, and D. Hadjimitsis, "3d documentation and bim modeling of cultural heritage structures using uavs: The case of the foinikaria church", *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. 42, p. 45, 2016.

[7] P. M. Hell and P. J. Varga, "Drone systems for factory security and surveillance", *Interdisciplinary Description of Complex Systems: INDECS*, vol. 17, no. 3-A, pp. 458–467, 2019.

[8] P. Oberlin, S. Rathinam, and S. Darbha, "Today's traveling salesman problem", *IEEE robotics & automation magazine*, vol. 17, no. 4, pp. 70–77, 2010.

[9] P. Min, *Binvox*, 2019. [Online]. Available: https://www.patrickmin.com/binvox (visited on 09/15/2021).

[10] W. Kabsch, "A discussion of the solution for the best rotation to relate two sets of vectors", *Acta Crystallographica Section A: Crystal Physics, Diffraction, Theoretical and General Crystallography*, vol. 34, no. 5, pp. 827–828, 1978.