Clustering based approach to single drone path planning in complex urban airspace

Summary

To enable safe and efficient UAS operations at lower altitudes, it is necessary to conduct airspace management and operations in urban airspace for a medium to large scale UAS traffic. A risk-based approach is to be adopted in traffic routing and scheduling, which should account for airspace restrictions and flight risk and safety constraints. This study includes deterministic and stochastic clustering based single drone routing, and deterministic and stochastic multiple drone routing and scheduling under single or multiple operators.

The current stage of this study focuses on deterministic cluster-based single drone routing, which gives the optimal path in relatively low urban airspace. Wind or any other features that cause uncertainties are not considered in this stage. San Francisco area was studied in this research. Drones fly direct Euclidean distance in high airspace where there is no fixed obstacle, and fly following the street network in very low airspace. For drones flying in the intermediate airspace where there are some obstacles that they can avoid on the path from origin to destination, the deterministic cluster-based approach was performed to generate the optimal shortest path. Unlike the high-altitude controlled airspace with few obstacles, the geospatial complexity derived from geometric variability of existing static obstacles such as buildings and terrain in intermediate airspace poses a new challenge in the UAS traffic flow management. The shortest path problem for drone in intermediate airspace is simplified to a 2D problem that we solve at several candidate altitudes. Altitude candidates were generated by clustering fixed obstacles in urban airspace, mainly buildings. The large number of fixed obstacles associated with individual buildings are preprocessed and clustered to form a smaller set of larger obstacles. The altitude of each obstacle cluster is the altitude of tallest building in the cluster. Altitude candidates are formed by the altitudes of each obstacle cluster. Fast marching algorithm is chosen to generate the shortest paths at each altitude candidate. The optimal altitude will then be determined by weighing the vertical cost to ascend to certain altitude and the horizontal travel cost of the shortest path at that altitude. Sensitivity analysis is performed with different number of obstacle clusters, and with different weights given to altitude in the clustering procedure. This study also compared the properties of different path planning algorithms to generate 2D shortest path.

The shortest path in presence of wind and other features causing uncertainties will be considered after the deterministic routing to form a stochastic routing problem, followed by 4D multiple drone routing in shared airspace with single or multiple operators.

Contents

1 Deterministic clustering-based single UAV routing

In Amazon's proposed airspace design for a drone highway, shown in figure 1, airspace between 200ft and 400ft is reserved for drones that can communicate with some sort of ground control, under 200ft reserved for consumer-type drones used for purposes like shooting video, and from 400ft to 500ft as a buffer between drones and planes. Inspired by Amazon's proposal, we are interested in path planning for single drone in the airspace with different levels. [1]

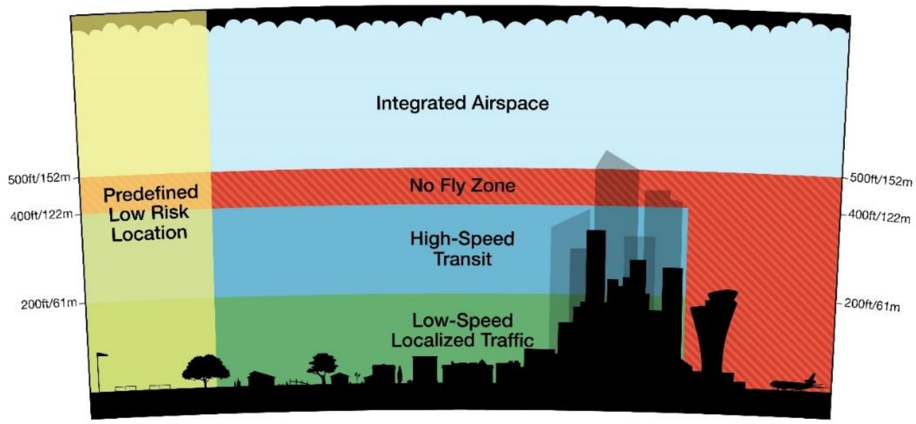

Figure 1: Amazon airspace design for drone highway

The airspace in our research can be divided into three levels by altitude, including higher airspace, intermediate airspace and lower airspace (see figure 2). The higher airspace has no static obstacles, so that drones can travel Euclidean distance directly from origin to destination. UAV traveling in the intermediate airspace needs to find optimal path to avoid certain obstacles on its way. Given the large number of obstacles in lower airspace and in order to ensure safety, it is better if the UAV can travel following the street network, making Manhattan distance a suitable approximation in many cases.

In path planning for a single UAS mission, one must choose between high, intermediate, and low airspace levels as well as a specific altitude within the chosen airspace level. A key tradeoff is that low altitude paths will tend to be longer because there are more obstacles to be avoided, whereas high altitude paths, while shorter, involve greater costs for ascent and descent. It is therefore very important to consider both the vertical climbing cost and horizontal travel cost to determine the optimal cruise altitude for a given UAV mission.

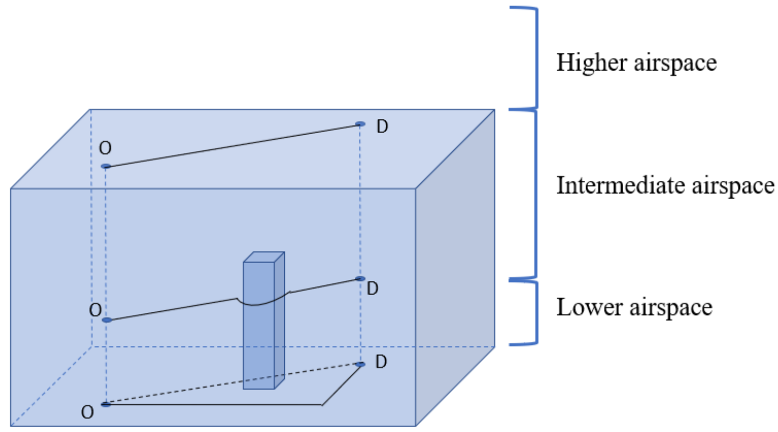

Figure 2: Path planning in different levels of airspace

This report focuses on the deterministic path planning problem of single UAV, with specific emphasis on the tradeoff highlighted above. For the purposes of our analysis make several simplifying assumptions. First, we assume there is no wind. Second, we assume that the UAV flies at a single altitude, vertically ascending at the origin and descending at the destination, and correspondingly that the cost of the route depends on the vertical distance and the horizontal distance of the route. Finally, we do not explicitly consider random deviations between the actual path of the drone and its nominal path. With these assumptions we can reduce our problem to a shortest path problem at different altitudes, and choosing the altitude that optimally balances horizontal and vertical cost.

1.1 Higher-level airspace

Since no uncertainty is considered under deterministic problem setting, UAVs that cruise in the higher-level airspace can travel directly from origin to destination without any static obstacles. The cruise distance is therefore the Euclidean distance between origin and destination. While extra distance may be required to for trajectory deconfliction in the multi-vehicle problem, we consider only a routing for a single UAV here.

1.2 Lower level airspace

The density and complexity of static obstacles increases as the altitude goes lower. In lower level airspace, available airspace for UAVs is limited. In addition, the static obstacles are very complex including different components other than buildings, for example, trees, street lamps, traffic signals, etc. Accordingly UAVs in lower level airspace will follow the street network, traveling the same route as ground vehicles. In many settings, horizontal distances in low level airspace may be well approximated by the Manhattan distance.

1.3 Intermediate airspace

In intermediate airspace, there is a limited set of static obstacles that diminishes as the UAV cruise altitude increases. A path planning approach is proposed to optimize the path of UAV to avoid the static obstacles in this airspace level.

The approach can be reduced from 3D path planning to 2D, since no wind or any uncertainty are considered. Only the cruise altitude needs to be determined for the UAV given OD pair. The optimal cruise altitude will be determined by weighing the vertical cost to ascend to a certain altitude and the horizontal travel cost of the shortest path at that altitude. It is necessary to generate a set of altitude candidates to compare the vertical and horizontal travel cost since exhaustive search over all altitudes is computational expensive. In order to generate the most appropriate altitude candidates that reflect major changes obstacle density, we propose to use a clustering approach in order to summarize the height and location of the numerous static obstacles.

Bases on the generated altitude candidates set, horizontal shortest paths that avoid the obstacles will then be generated for each altitude candidate by a fast marching algorithm. We will then be able to compare the vertical and horizontal costs to decide the optimal travel altitude and cruise path at that altitude.

This report discussed the obstacle clustering methodology for altitude candidate generation, shortest travel path generation, and optimal altitude analysis.

1.3.1 Static obstacles clustering and altitude candidates

In this subsection, we generate a set of altitude candidates by clustering the obstacles. We take San Francisco as out study area. Our research doesn't consider the geographical ground level in current stage, which means we assume San Francisco is in a flat plain and only the height of buildings is considered. The original static obstacles data of San Francisco is shown in figure 3. By looking at the geographical characteristics of buildings in figure 3, it is not efficient to generate obstacle free shortest paths directly based on exact spatial locations of each building, since the narrow areas between buildings are not usable and the procedure is computationally expensive. This motivates the clustering of obstacles before generating the shortest path.

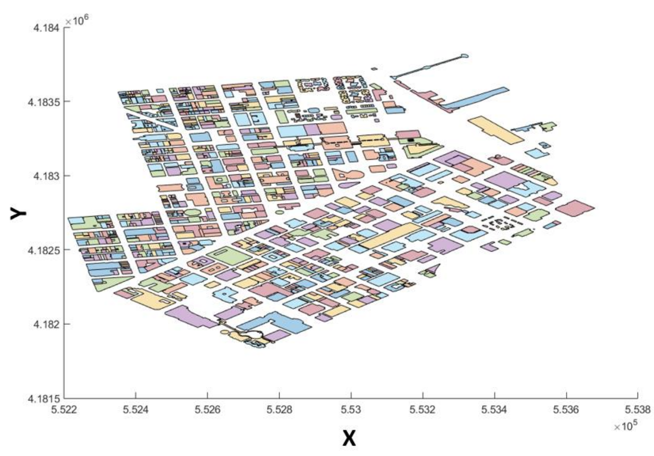

Figure 3: Sky view of San Francisco area static obstacles in projected coordinate system: EPSG 32610, WGS 84 / UTM zone 10N, in meter

The K-means clustering algorithm is chosen to perform clustering over all buildings in the study area. For purposes of clustering we first generate the minimum rectangle containing the footprint of each building. The four vertices' coordinates of the minimum rectangle and the height of building are then used for clustering. Thus, each building is summarized by nine variables: The X and Y coordinates values of four building vertices plus the height. While all variables are in units of meters, height is unique because heights vary far less than the X and Y coordinates and the height of a cluster will be determined by the height of the tallest building in that cluster. For this reason, building heights are rescaled by different factors, from 10 times to 100 times. We presented the results of 20, 30, and 40 clusters, with scale of 10 times and 50 times in this subsection.

After clustering, the convex hull of buildings belonging to the same cluster forms an aggregated obstacle, which will be used to generate cruise shortest path. On the one hand, more airspace will be made unavailable as a result of being included in the polygons of aggregated obstacles, when the number of clusters is small. On the other hand, it will be more computational expensive to generate a shortest path when the number of clusters increases. With a greater rescaling factor, taller buildings will be more likely to be clustered in the same aggregated obstacle, instead of buildings that are geographically closer. Points in different clusters intermingle more in the case with more scaling.

In order to ensure safety, keep-out geofencing, the safety distance that drones are required to keep away from buildings, is considered when we generate aggregated obstacles based on the clustering results. We simply add the keep-out geofencing distance by expanding the obstacles outward certain distance. All the following research is using the aggregated obstacles with 10 meters keep-out geofencing distance. The height of new aggregated obstacles is the maximum height of the buildings within each cluster. The altitude candidates are the set of aggregated obstacle heights.

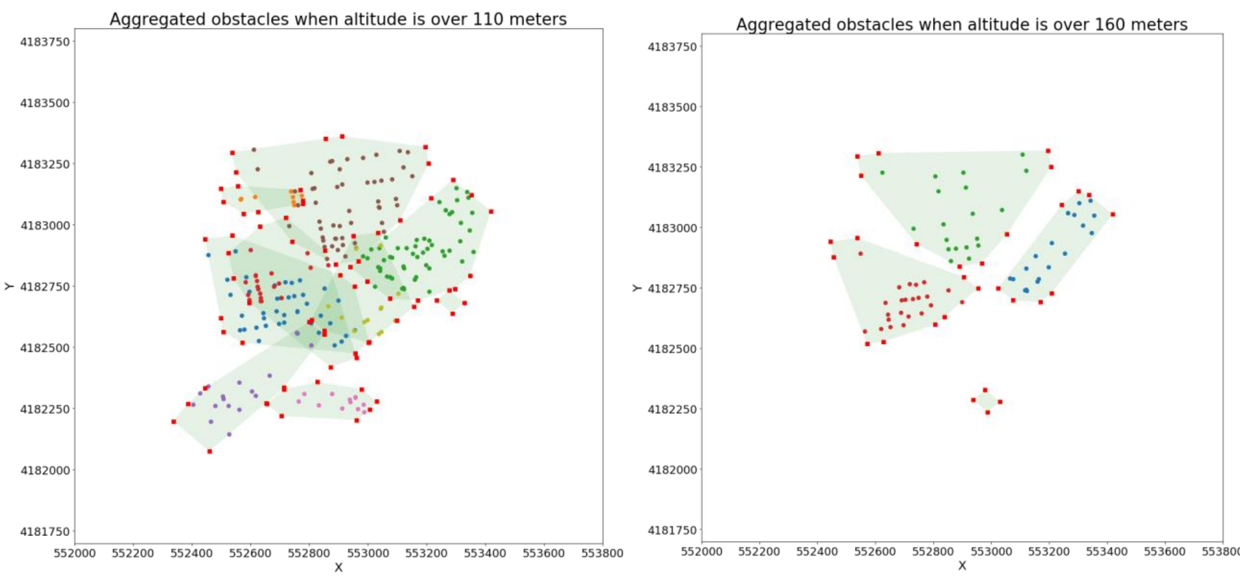

Figure 4: Sky view of aggregated obstacles at different altitudes

Figure 4 shows an example of aggregated obstacles at different altitudes. Red dots are the boundary points of the new aggregated obstacles. Dots with different colors within the boundary are the building vertices belong to the cluster, and the cluster obstacle area is filled in green. The left figure shows the aggregated obstacles at the altitude of 110 meters and the right figures at

160 meters. The number of aggregated obstacles decreases and there is more available airspace, as altitude increases.

Table 1 shows the total volume of obstacles in study airspace under the cases of different numbers of cluster from 20 to 40 and different rescaling levels from 10 to 50 times. As shown in the table, the total volume of obstacles decreases with larger number of clusters, which is consistent with our expectation. More available airspace will be counted as obstacle in the convex hull of buildings within same cluster label when we have a smaller number of clusters. The rescaling factor of building height doesn't give a simple increasing or decreasing pattern to the total volume of obstacles. Buildings with similar height are more likely to be in the same cluster than with closer geographical distance. With larger rescaling factor, more available airspace between buildings will be counted as obstacles, but less available airspace from height difference of close buildings will be counted as obstacles. Therefore, the total volume of obstacles with different rescaling factor fluctuates as the rescaling factor changes. In addition, the rescaling factor of building height has larger influence on the total volume of obstacles than the number of clusters based on the data.

Table 1: Total volume of obstacles in study airspace under the cases of different numbers of clusters and rescaling levels

Total volume of obstacles in airspace (m^3)		Number of clusters		
		20	30	40
Rescaling factor of building height	10	3.147×10^8	2.485×10^8	2.260×10^8
	20	2.667×10^8	2.289×10^8	2.173×10^8
	30	2.450×10^8	2.254×10^8	2.161×10^8
	40	2.434×10^8	2.298×10^8	2.200×10^8
	50	2.383×10^8	2.231×10^8	2.137×10^8

1.3.2 Optimal travel route by fast marching algorithm

Based on the altitude candidates from previous section, the optimal cruise shortest path will be generated at each altitude in the altitude candidates set in this subsection.

Fast Marching algorithm is used to generate the shortest UAV cruising path. The main idea of Fast Marching algorithm is to exploit a fast heapsort technique to systematically locate the proper grid point to update, so that one need never backtrack over previously evaluated grid points. It sweeps through a grid of N total points in N log N steps to obtain the evolving time position of the front as it propagates through the grid [2]. Compared to the traditional Dijkstra algorithm or A* algorithm, Fast Marching algorithm replaces the graph update by a local resolution of gradient descent, calculated by the Eikonal equation, instead of only considering eight directions of neighbors (forward, backward, left, right and four diagonals). This reduces significantly the grid bias, and converge to the geodesic distance when the grid step size tends to zero. The computation time of fast marching is acceptable, and it yields a better approximation of the true shortest path.

In our research, the grid size is set to be 1 meter and the step size is set to be 10 meters, 10 times of grid size. Figure 5 shows shortest path results for the case with 40 aggregated clusters and 10x height rescaling. The dark areas in the plots represents all aggregated obstacles at a given altitude. Even though every aggregated obstacle is a polygon, the dark blue area is not necessarily convex since various aggregated obstacles are overlapped with each other. This doesn't influence the implementation of Fast Marching algorithm. The same OD pair is given in four plots, where red dot represents origin and green dot represents destination. As the altitude increases, some obstacles disappear, leaving more available airspace to travel. The shortest cruise path decreases accordingly.

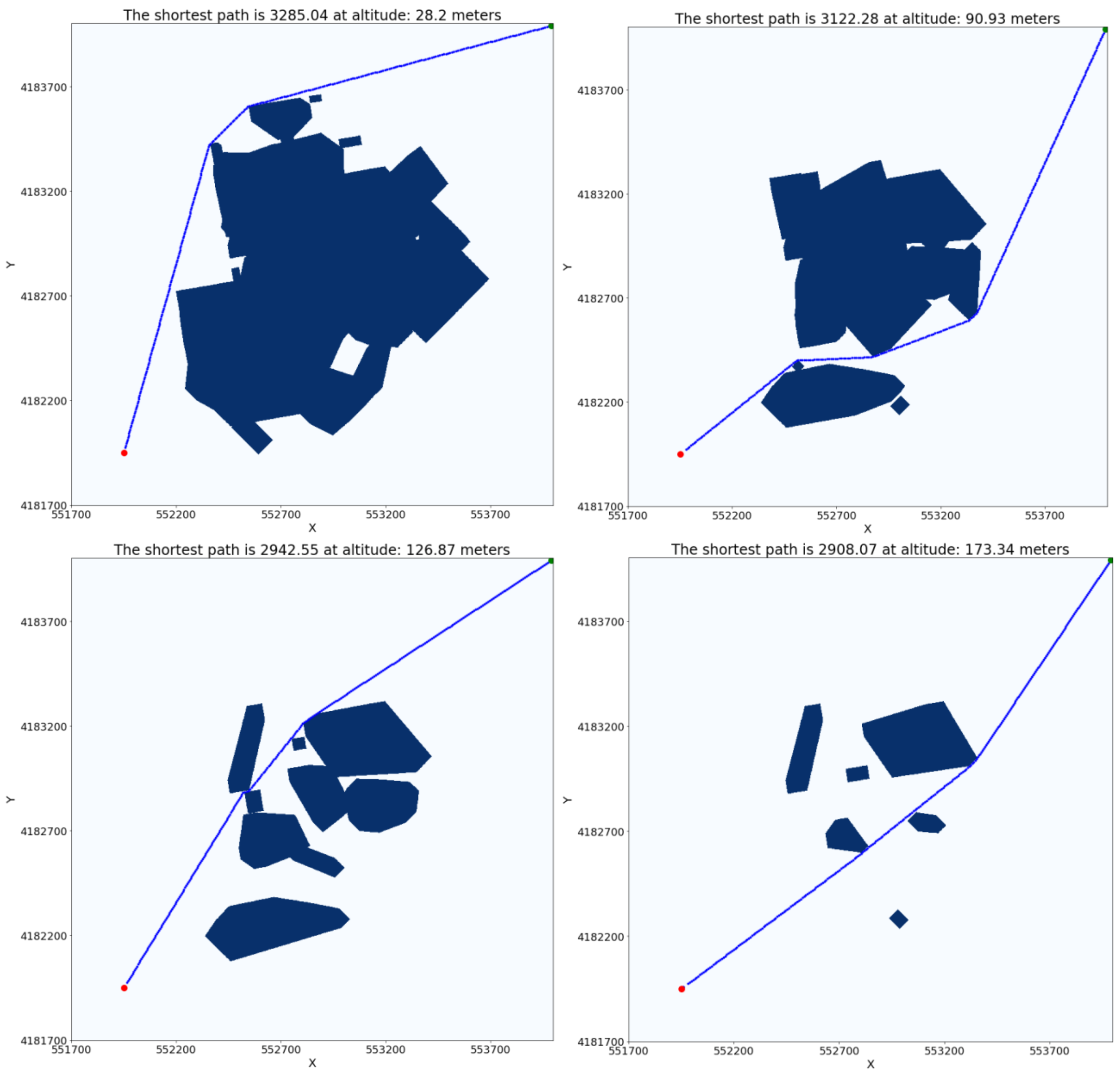

Figure 5: Shortest path example with 40 clusters and 10 times scaling of building height at four different altitudes given the same OD pair (sky view)

1.3.3 Determine optimal cruise altitude

Shortest travel paths at different altitude candidates were generated in the previous subsection. In order to decide the optimal travel altitude, we are interested in how the length of the shortest path changes with different altitudes. Figure 6 plots the pattern of the length of shortest path at different altitude candidates under the case with 30 clusters and 10x rescaling of building height. The red dots represent the data at each altitude candidate, and we superimpose step lines on the plot. Based on the shortest path length profile in this case, we can determine the optimal travel altitude by weighing the vertical and horizontal cost. Known the ratio of vertical and horizontal travel cost, for example, the slope of the black line in the figure, the tangent point of the cost ratio line and our plot will give the optimal cruise altitude. It is possible there are multiple optimal solutions as figure 6 shows.

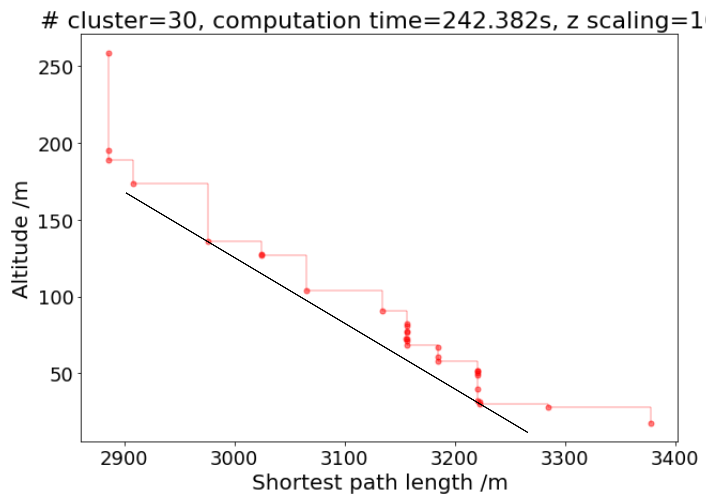

Figure 6: Shortest path change at different altitude with 30 clusters and 10 times scaling of building height

1.3.4 Experimental design

The section performs the sensitivity analysis of the number of clusters and the scaling levels of building height for clustering. We analyze how the number of clusters will influence the shortest path change as the altitude changes, and how the scaling level will affect the shortest path change at different altitudes.

1.3.4.1 number of clusters

The pattern of the shortest path length at each altitude candidate for different number of clusters is shown in figure 7 both separately and together. For figure 7 we assume xx height rescaling. When we look at the first three separate plots, we notice there are more candidate altitudes, and accordingly more points plotted, as the number of clusters increases. Computation times with the number of clusters because of increases in both the number of candidate heights and the number of obstacles. From the comparison plot with all patterns drawn together, we see that blue plot is below red plot, and red plot is below green plot. This is because as the number of clusters increases, there is more available airspace the UAV can travel. For a given altitude, the shortest path length with larger number of clusters will be less than or equal to that with smaller number of clusters. Therefore, the shortest path length with larger number of clusters drops faster as the altitude goes higher, which is consistent with the results shown in the last plot in figure 7. Figure 7 also shows that path lengths are different only over a narrow altitude range of 100 to 200m. Outside of this range, the plots overlap.

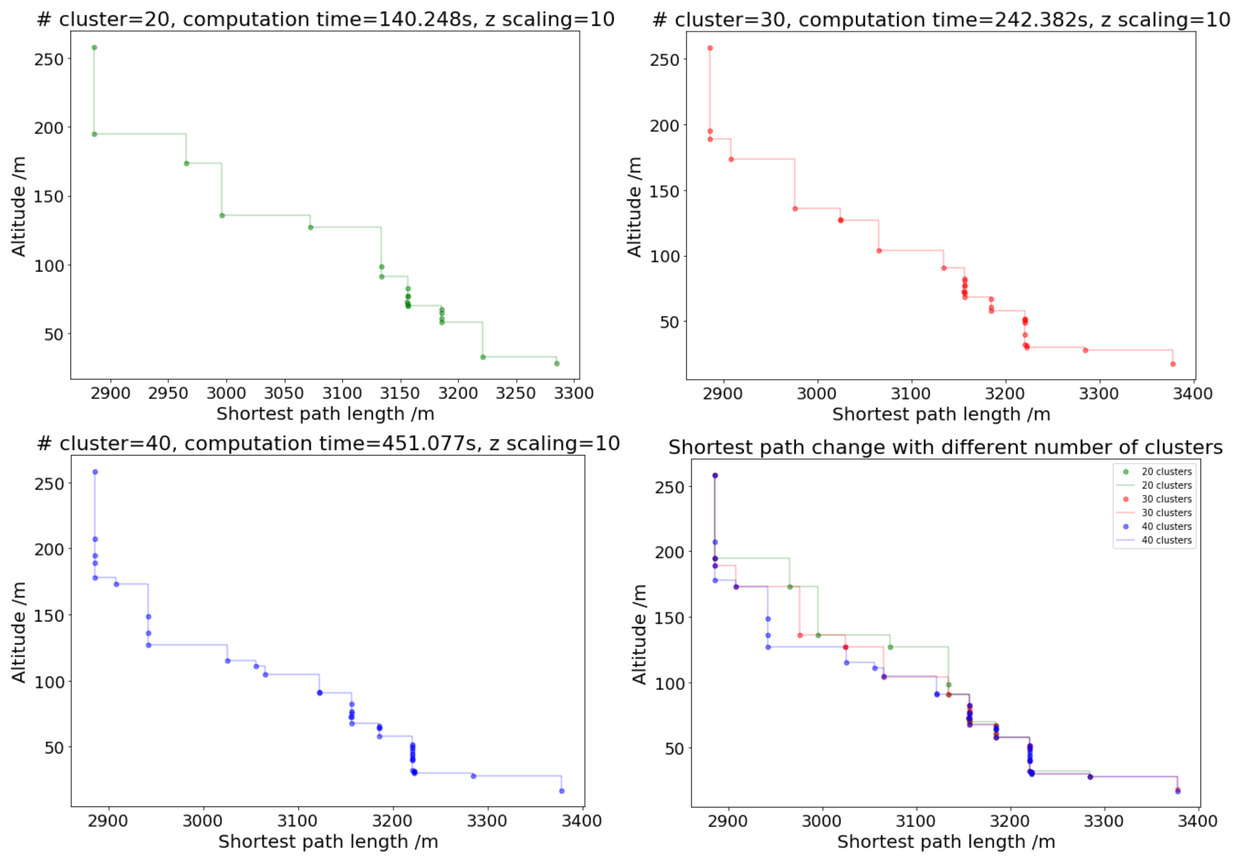

Figure 7: Shortest path length at different altitudes with different number of clusters and with 10 times scaling of building height, and comparison results

1.3.4.2 Scaling of building height

The scaling levels of building height for clustering of obstacles have been analyzed in this subsection. In figure 8, shortest path length patterns with 10x, 30x and 50x rescaling of building height with 30 clusters are presented. Based on the last comparison plot, the effect of rescaling on shortest path length does not exhibit a clear trend. The more we scale, the more likely buildings with the similar height are clustered together. The available airspace between buildings with similar height will be counted as obstacles in this case. However, if we don’t scale enough, buildings close to each other but with very different height will be clustered together. The available airspace of the height difference between buildings will be counted as obstacles.

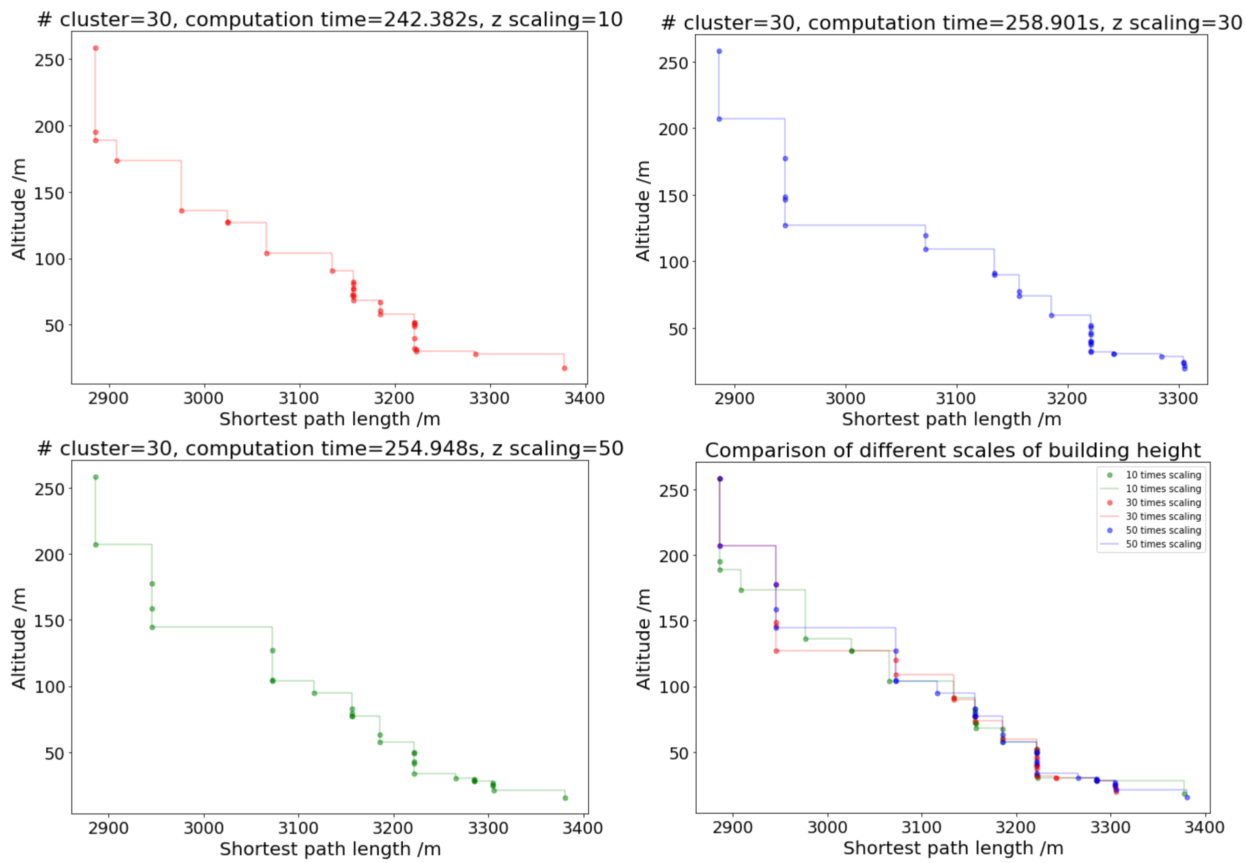

Figure 8: Shortest path length with different scaling levels with 30 clusters at different altitudes, and comparison results

2 Future research

2.1 Short-term

In the current stage of research, we show the preliminary results of deterministic clustering-based single drone routing. Before entering the next step, we will improve the clustering algorithm of obstacles, and compare different 2D routing algorithms for shortest path.

For the clustering algorithm, we are currently using K-means algorithm by clustering the X and Y coordinates of building vertices and altitude of buildings. Since different weights given to the altitude of buildings result in different clusters, it is hard to decide the proper weight of altitude. We are working on a potential cluster algorithm that gives the cluster label of obstacles to optimize the amount of available airspace.

Regarding the path planning algorithm, Fast Marching was used. We will compare the performance of different algorithms in future research. A* is a widely used traditionally navigation and path planning algorithm. Its computation complexity is log(N) where N is the optimal heuristic, the exact cost to get from origin to the destination. The computation time highly depends on the heuristic, and the complexity of obstacles also affect the computation time. Comparing optimal computation complexity, A* is faster than Fast Marching. However, Fast Marching gives more optimal path because it uses gradient descent to update each step. A* only considers 8 directions (forward, back, left, right, diagonals) to update each step.

Furthermore, the heuristic of A* algorithm is very sensitive to the complexity of obstacles. The computation time using A* in our research with complex obstacles might not reach the optimal O(logN). It makes these two algorithms very competitive in computation time. Further research will compare the performance of both algorithms. In addition, visibility graph methods will be another potential algorithm to be considered. The complexity of visibility graph methods ranges from O(n^2*log(N)) to O(n*log(N)+E). (N is number of nodes, E is number of edges).

2.2 Long-term

This section describes the long-term future research in next two years.

1. Stochastic clustering-based single drone routing

The current deterministic clustering-based single drone routing assumes no wind or any uncertainty. Stochastic version will be considered as next step, including path planning in presence of wind and management of risk and uncertainties.

1) Routing in presence of wind

Wind effect can not be ignored both in manned aerial system and UAS for path planning. The main concern of wind is that it increases the motion deviation of UAV. In traditional manned aircraft system, the tail wind helps save energy and time, which will not be considered as a benefit in UAS for small UAVs. With low altitude wind data, we will propose path planning algorithm to generate better path under different wind situations.

2) Management of risk and uncertainties

Assessing and ensuring the safety of an emergent UAS operation is a complex and difficult problem due to the numerous factors that must be considered. JARUS [3] proposed a bow-tie model for risk assessment and NASA [4] proposed risk matrix. The risk analysis process is undertaken to provide assurances that the risks associated with the operation of unmanned aircraft systems have been managed to acceptable levels. In our research, we will consider different uncertainties and risks in our path planning model. The generated optimal path will ensure certain level of safety, considering both risk and uncertainties instead of just giving the shortest or minimum energy cost path.

2. 4D multiple drone routing in shared airspace

After working on stochastic single drone routing, we will move to multiple drone routing in shared airspace with manned aircrafts. Multiple drone routing will be considered under the case of single operator and multiple operators. Routing, traffic management, uncertainties and risk management will be included in multiple drone routing.

1) Single operator

4D multiple UAVs path planning will be done under single operator as the first step in this section. We will mainly focus on routing and traffic management without the complexity of allocating resources and priority among different operators. Conflict detection and resolution will be performed to generate optimal path for all UAVs in the system. Inspired by the Ground Delay Program (GDP) in manned aircraft system, ground holding might be applied to UAS as well to manage traffic. The uncertainties and risks including the effect of wind and collision risk will be considered in the stochastic version of model.

a. 4D multiple drone routing
b. Drone traffic management with ground holding
c. Stochastic version

2) Multiple operators

Under multiple operators, 4D multiple UAV routing and traffic management will be performed as well, also considering the uncertainties and risks in stochastic version. Different from single operator, the priority and collaboration will be considered for different operators in the UAS. Routing and traffic management decisions will be distributed between the traffic manager and the individual UAV operators.

a. 4D multiple drone routing
b. Drone traffic management with ground holding
c. Stochastic version

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