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Quality-Aware Trajectory Planning of Cellular Connected UAVs

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ABSTRACT

The use of Unmanned Aerial Vehicles (UAVs) is becoming common in our daily lives and cellular networks are effective in providing support services to UAVs for long-range applications. The main target of this paper is to propose a modified form of well-known graph search methods i.e., Dijkstra and A-star also known as A* algorithm, for quality-aware trajectory planning of the UAV. The aerial quality map of the propagation environment is used as an input for UAV trajectory planning, and the quality metric considered for this work is Signal to Interference plus Noise Ratio (SINR). The UAV trajectory is quantified in terms of three performance metrics i.e., path length, Quality Outage Ratio (QOR), and maximum Quality Outage Duration (QOD). The proposed path planning algorithm aims at achieving a trade-off between the path length and other quality metrics of the UAV trajectory. The simulations are performed using an agreed 3GPP macro cell LOS scenario for UAVs in MATLAB. Simulation results illustrate that the proposed algorithm significantly improves the QOR by slightly increasing the path length compared with the naive shortest path. Similarly, the outage avoidance path achieves high QOR at the expense of large path length, and our proposed method finds a compromise and provides an optimal quality-aware path.

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CCS CONCEPTS

• **Theory of computation → Shortest paths**.

KEYWORDS

UAV, Cellular, Trajectory planning, Simulations, Graph search.

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1 INTRODUCTION

The utilization of Unmanned Aerial Vehicles (UAVs) has gained significant traction over the past few years [5, 11]. Their usage can be seen in numerous applications ranging from surveillance and disaster management to video streaming and monitoring of the environment. The adoption of UAVs in varied application scenarios may require non-interrupted connectivity from cellular networks. This holds true particularly for military and security-critical applications, where there is a strict requirement for data rate, packet loss, and coverage outage.

Generally, commercial UAVs establish their wireless communication link with the Ground Control Stations (GCSs) operating at 2.4 GHz frequency. However, it is challenging to provide low-latency and ultra-reliable communication for long-range UAV applications with a single ground controller. The seamless mobility and ubiquitous accessibility offered by the cellular networks make them a suitable candidate for controlling the UAV, and for high-speed data transmission to and from UAVs [8]. To fully utilize the unprecedented opportunities of cellular-enabled UAVs, various challenges related to high-altitude coverage should be first addressed.

Considering the potential of cellular networks in assisting UAV communication, 3GPP made a study related to enhanced Long Term Evolution (LTE) support for connected drones [2]. Currently, mobile operators are working on optimizing cellular networks for offering various UAV-based services [14]. In order to support long-range applications of UAVs, the UAV manufactures are providing the support of LTE connectivity for controlling the UAV and for sending and receiving the data. UAVs equipped with high-definition cameras may need to transmit video in real-time during rescue or surveillance operation, and hence, they can accomplish this operation by using LTE connectivity provided by the mobile operators [6, 10]. Cellular networks encounter various challenges when it comes to high-altitude aerial coverage for UAVs. Generally, the cellular networks are optimized for serving terrestrial users, and thus do not guarantee high Quality of Service (QoS) and seamless aerial coverage for UAVs [10]. The wide spectrum available at Millimeter Wave (mmWave) frequencies offers a promising solution for real-time ultra-high-speed transmissions for UAVs.

The Optimal positioning and trajectory planning of UAVs is discussed in [3, 7, 16] for improving the connectivity and quality of cellular-enabled UAVs. The channel gain map-based approach is used in [7] for learning the UAV trajectory and for maximizing the communication throughput. A recent study on cellular-connected UAVs[16] also employed aerial connectivity coverage map approach in graph search method for finding the coverage hole detour path of flying UAV. In this paper, we have proposed a modified form of well known graph-search methods i.e., Dijkstra and A* search method [15] for finding the optimal trajectory of a UAV for source-destination pair. There is a strong relationship between the radio propagation conditions and the flying altitude of UAVs. We have proposed to use an aerial quality map to alter a cost function used in well-known graph search methods for finding the quality-aware trajectory of UAV.

The rest of the paper is organized as follows. Section II discusses the problem definition and explains a system model. In Section III, we present our proposed algorithm for trajectory planning and also discuss other pathfinding cases. Simulation tools, models, and environments are discussed in Section IV. In Section V, we present the simulation results followed by discussion. Finally, Section VI concludes a paper.

2 PROBLEM DEFINITION AND SYSTEM MODEL

2.1 Problem Formulation

Several applications involve a long-range flight of UAVs. Cellular networks are commonly used for controlling the UAV, and for other services i.e., data transfer in those long-range cases. The cellular coverage is provided with several base stations by the mobile operator in an area. However, in a practical network, there still exist holes from signal coverage/quality point of view. The target for a UAV is to fly at a specific height e.g., 200 m above the ground, from the source location to the destination location while maintaining a certain quality of service i.e., Signal to Interference plus Noise Ratio (SINR) and the path length. The aerial quality map at 200 m can be provided by the radio propagation prediction tool.

2.2 System Model

UAV mobility space: We have only considered the horizontal mobility of the UAV. The two-dimensional horizontal space is divided into N and M equally spaced intervals along the x and y axis, respectively, yielding a grid of $N \times M$ rectangles. Each grid unit $\mathbf{u}$ has a Cartesian coordinate form i.e., (i, j), and the set for all grid unit coordinates is denoted as $G = \{(i, j)\big| \; 0 \le i \le N-1, 0 \le j \le M-1, i, j \in \mathbb{Z}\}$.

UAV action space: At any grid position, the UAV is allowed to move in one of the possible eight directions i.e., forward, backward, right, left, right-forward, left-forward, right-backward, and left-backward, the later four movements are the diagonal movements. Here, these movements are treated as actions. The set for horizontal and vertical movement action in 2D grid is $H = \{(0, 1), (0, -1), (1, 0), (-1, 0)\}$, and the set for diagonal movement action is $D = \{(1, 1), (-1, 1), (1, -1), (-1, -1)\}$. The set for all the actions is denoted as $A = \{H \cup D\}$. Let $\mathbf{u}_k$ denotes the position of the UAV in space grid at k^{th} state, the position of the UAV at $(k+1)^{th}$ state can be given by the state transition equation as shown in Eq. 1.

$$\mathbf{u}_{k+1} = \mathbf{u}_k + a, \mathbf{u}_k, \mathbf{u}_{k+1} \in G, a \in A. \tag{1}$$

Thus, the trajectory or path $\mathbf{p}$ of the UAV flying from the source to the destination can be determined by a sequence of $K+1$ states,

$$\mathbf{p} = \left\langle \mathbf{u}_k \middle| \mathbf{u}_k \in G, k = 0, 1, 2......K \right\rangle \tag{2}$$

where K is the number of states a UAV moves from the source to the destination point, and $\mathbf{u}_0 = (i_s, j_s)$ and $\mathbf{u}_K = (i_d, j_d)$ are the grid coordinates of the source and destination point, respectively.

UAV speed: It is assumed that UAV flies at a constant speed V_{const} as given in Eq. 3:

$$V_{const} = \frac{\left\| \mathbf{u}_k - \mathbf{u}_{k-1} \right\|}{\Delta t_{k,k-1}}, k = 1, 2, 3......K \tag{3}$$

where $\Delta t_{k,k-1}$ is the time required by the UAV to move from $(k-1)^{th}$ state to k^{th} state, and $\|.\|$ represents the Euclidean distance between the $(k-1)^{th}$ and k^{th} state.

2.3 Aerial Quality Map

Our target is to plan a quality-aware trajectory of UAV, and for this purpose, an aerial quality map is used as an input. By using the aerial quality map the UAV learns about the quality holes and can avoid going into bad quality areas while flying from source to destination. The map-based approach has been previously used in literature to position the UAV relay node for improving the cellular connectivity [4], and for the trajectory optimization of the UAV base stations [7]. The quality aerial map at a certain height can be generated by different commercial planning tools/software for given network layout and map data. The aerial quality map is also discretized into N and M equally spaced gaps along the x and y axis, respectively, as done in the case of UAV mobility space. The aerial quality map characterizes whether at each grid unit in UAV mobility space the cellular network is able or not able to provide services above or equal to certain quality threshold (δ). The aerial quality map is a binary matrix represented as $\mathbf{M} \in \{1, \alpha\}^{N \times M}$, where $m_{i,j} = \alpha$ means that the cellular network quality is below the quality threshold δ at the grid unit $u = (i, j) \in G$, otherwise $m_{i,j} = 1$. For a UAV with flying path p, we have defined a sequence Q^p to indicate the quality status of the UAV along the trajectory and is given as:

$$\mathbf{Q}^p = \left\langle Q_k^p = m_{i,j} \middle| (i, j) = \mathbf{u}_k, \mathbf{u}_k \in \mathbf{p}, k = 0, 1, 2...K \right\rangle \tag{4}$$

2.4 Performance metrics

We have considered three performance metrics to quantify the trajectory of the UAV i.e., path length, Quality Outage Ratio (QOR), and maximum Quality Outage Duration (QoD). The path length is defined as the total length in meters the UAV covers while following the trajectory from the source to the destination point, and that can be calculated by using eq. 2. the quality outage ratio is similar to the connectivity outage ratio introduced in [16]. The quality outage ratio in percentage is defined as the ratio of the grid units with cellular quality lower than the quality threshold to the total number of grid units the UAV covers along the trajectory. For a UAV with quality indicator sequence Q^p along the UAV trajectory p, the QOR is defined as:

$$QOR = \frac{\sum_{k=0}^{K} L_k^p}{K+1} \times 100, L_k^p = \begin{cases} 0 & if \quad Q_k^p = 1 \\ 1 & if \quad Q_k^p = \alpha \end{cases} \tag{5}$$

Another metric considered for the analysis is the QOD, and is defined as the length of the consecutive quality holes in the UAV trajectory. There can be several QOD values $\{QOD_{\mathbf{p}}^{(l)} : l = 1, 2, 3, ...L\}$ for single UAV trajectory path $\mathbf{p}$, as there can be several patches of service outage during the flight. Each $QOD_{\mathbf{p}}^{(l)}$ is defined as:

$$QOD_{\mathbf{p}}^{(l)} = \sum_{k=i^{(l)}}^{j^{(l)}} L_k^p, \quad L_k^p = 1 \quad if \quad Q_k^p = \alpha, \quad i^{(l)} \le j^{(l)} \le K \tag{6}$$

3 TRAJECTORY PLANNING ALGORITHM

In this paper, the target is to plan the trajectory of the UAV while keeping the path length short and maintain a certain level of QOR and maximum QOD. The zero value of QOR means that the quality of the UAV was always better than the quality threshold, and UAV did not experience any quality hole during the flight. However, in this case, the trajectory followed by the UAV not necessarily shows the shortest path between the two points. Here, we are presenting a general algorithm based on graph search method. The graph is a collection of nodes which are connected between one another, and the connection between the nodes is called an edge, where each edge is associated with weight. We define an undirected graph $S = (V, E)$, where V is the node-set and it comprises all the grid units in the UAV mobility space, and E is the edge set and represents the connection between the nodes.

$$V = G, \tag{7}$$

$$E = \{e = (\mathbf{u}, \mathbf{v}) | \mathbf{u}, \mathbf{v} \in V, \mathbf{v} = \mathbf{u} + a, a \in A\} \tag{8}$$

Each edge $e \in E$ is associated with weight $l(e)$ and this weight is used to compute the cost of the flying UAV in graph representation. The weight $l(e)$ is the function of the distance between the grid units and is defined as,

$$l(e) = \begin{cases} d_1 & if \quad \mathbf{v} = \mathbf{u} + x, \mathbf{u}, \mathbf{v} \in V, x \in D \\ d_2 & if \quad \mathbf{v} = \mathbf{u} + x, \mathbf{u}, \mathbf{v} \in V, x \in H \end{cases} \tag{9}$$

where d_1 is the weight/cost of the diagonal movement, and d_2 is the cost of the horizontal or vertical movement in the movement space grid. The A star algorithm a.k.a A* search algorithm was proposed in [9] to find the shortest path with minimum cost using graphs. The A* search algorithm is the enhanced form of Dijkstra's shortest path algorithm. Here, in this paper we are proposing a modified form of A* search algorithm to handle the problem of quality aware path planning in flying UAV scenario. The generalized expression of proposed algorithm for evaluating the weight at each node $\mathbf{v} \in V$ is given as follows:

$$w(\mathbf{v}) = m(\mathbf{v})g(\mathbf{v}) + m(\mathbf{v})h(\mathbf{v}) \tag{10}$$

where $g(\mathbf{v})$ is the true optimal cost from the source node $\mathbf{s} = \mathbf{u}_0 = (i_s, j_s)$ to the current node $\mathbf{v}$, and $h(\mathbf{v})$ is the heuristic estimate of the cost from current node v to the destination node $\mathbf{d} = \mathbf{u}_K = (i_d, j_d)$, and $m(\mathbf{v})$ is the biasing factor used to alter the cost of the edge and it is coming from the aerial quality map. For the nodes with quality level above the quality threshold δ the true optimal and heuristic weight factors are multilplied by 1, and for the nodes with quality level below the quality threshold the true optimal and heuristic weight factors are biased with factor α. The true cost $g(\mathbf{v})$ from the source node to the current node $\mathbf{v}$ can be obtained by summing the weights of the edges of the path nodes, and for the heuristic estimate of the cost $h(\mathbf{v})$ we have considered the Euclidean distance i.e., the shortest distance or as the crow flies between the current node and destination node. The calculation of $g(\mathbf{v})$ and $h(\mathbf{v})$is done as:

$$g(\mathbf{s}) = 0 \tag{11}$$

$$g(\mathbf{v}) = g(\mathbf{u}) + l(\mathbf{u}, \mathbf{v}) \tag{12}$$

$$h(\mathbf{v}) = \left\| \mathbf{v} - \mathbf{d} \right\| \tag{13}$$

where $\mathbf{u}$ is the last node in the path from the source node $\mathbf{s}$ to the current node $\mathbf{v}$. The generalized model given in eq. 10 is reduced to Dijkstra path search model by assuming $h(\mathbf{v}) = 0$.

3.1 Cases

In this subsection, the path planning cases we have defined for the analysis are presented.

Shortest path: The first trajectory planning method we have considered is the basic and the most widely used "Shortest path" algorithm. It takes the shortest route for the UAV to reach the destination point from the source without considering any quality constraint.

Outage avoidance path: In the second case, UAV takes into account the quality metric and completely avoids the outage by not going into quality/coverage holes. In this case, $m(\mathbf{v}) = 1$ and $m(\mathbf{v}) = \infty$ for nodes with above and below the quality threshold, respectively.

Proposed quality-aware biased path: In the last case, a compromise is made between the shortest path and the outage avoidance path. In the proposed quality-aware biased path algorithm, the weight of the nodes with quality level below the threshold is altered with the biasing factor α, and $1 < \alpha < \infty$. The biasing factor varies the path length and QOR of the path and is adjusted according to the requirement of the path planner.

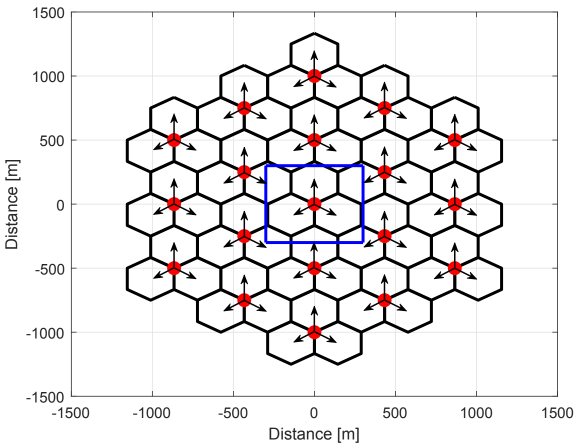


Figure 1: Simulation scenario.

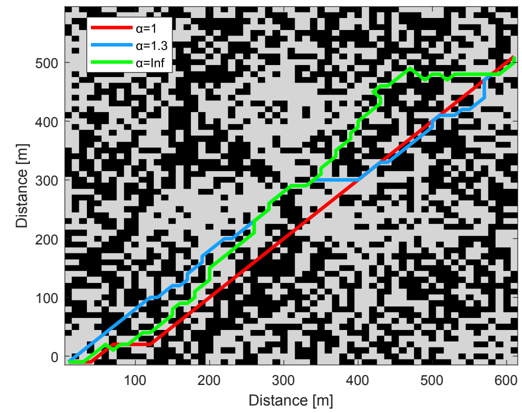
4 SYSTEM MODEL AND SIMULATIONS

4.1 Simulation Environment

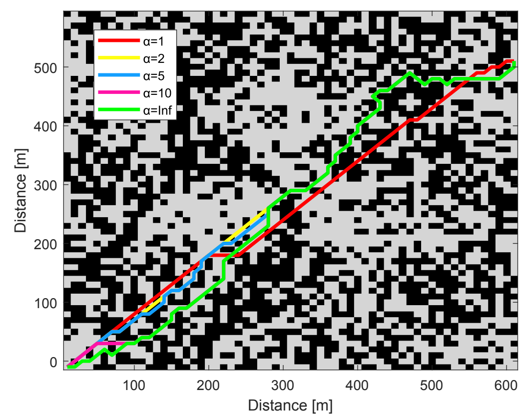
In this research work, We have used MATLAB as a simulation tool, both for generating the aerial coverage/quality map data and for finding the optimal path of the UAV. We have considered an agreed 3GPP urban environment scenario with a greenfield macro cell deployment. The network layout follows a cloverleaf tessellation [12, 13] with nineteen macro sites having an intersite distance of 500 m. Each macro site comprises three sectors with fixed 120° angular separation in an azimuth plane as shown in Fig. 1. The Base Station (BS) antenna height is set to 25 m, and the frequency of operation is 28 GHz, utilizing 20 MHz system bandwidth. The focus area considered for this study is highlighted with a blue rectangle as shown in Fig. 1. There is a grid of 61×61 UAV location points with a resolution of 10 m in the focus area. Therefore, each grid unit represents an area of 10 $m \times 10$ m. The height of the UAV is set to 200 m, and it is assumed that UAV stays in Line of Sight (LOS) with the BSs as UAV flies at 200 m. The detailed description of the path loss and models used for estimating the received signal power of UAV from different BSs can be found at [1]. The general simulation parameters are summarized in Table. 1.

Table 1: General simulation parameters

Parameters	Unit	Value
Channel model		3GPP UM_a
UE type		UAV
Intersite distance	m	500
Frequency	GHz	28
System bandwidth	MHz	20
Cell TX power	dBm	46
TX antenna height	m	25
UE height	m	200
Antenna model		3GPP extended model



(a)

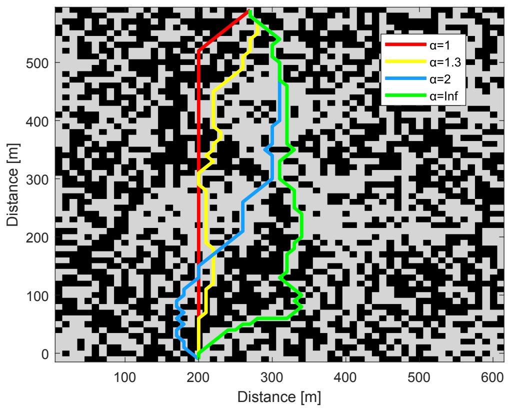


(b)

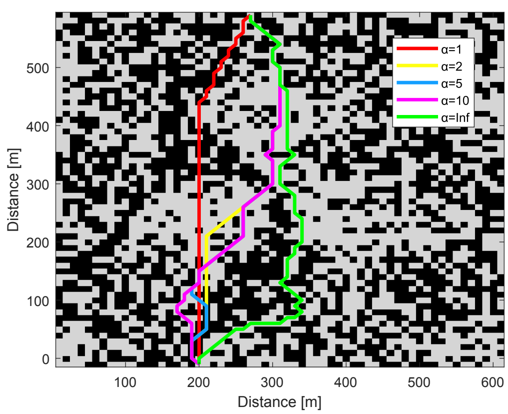
Figure 2: UAV trajectories for source-destination pair 1 with different biasing factor, (a) Modified Dijkstra algorithm, (b) Modified A* algorithm.

5 SIMULATION RESULTS AND DISCUSSION

In this section, we evaluate the performance of different trajectory planning algorithms for two different Source-Destination (S-D) pairs. We have considered modified Dijkstra and modified A* algorithm for the analysis. Fig. 2 shows the aerial quality map of the focus area. The gray color of the map shows the grid units with coverage, and the black color of the map shows the grid unit with quality/coverage holes. The aerial map was obtained by using the quality threshold of -3 dB SINR. Fig. 2(a) shows three UAV trajectories for S-D pair 1, whereas those trajectories were obtained by using a modified Dijkstra algorithm with three different values of α. The path with $\alpha = 1$ corresponds to the shortest path, $\alpha = Infinity$ corresponds to detour or outage avoidance path, and $\alpha = 1.3$ is a biased quality-aware path. It can be seen that the shortest path did not consider any quality constraint and follows a trajectory that provides minimal flying distance. On the other hand, the outage avoidance path strictly takes into account the quality metric and took the longest path to reach destination while avoiding coverage

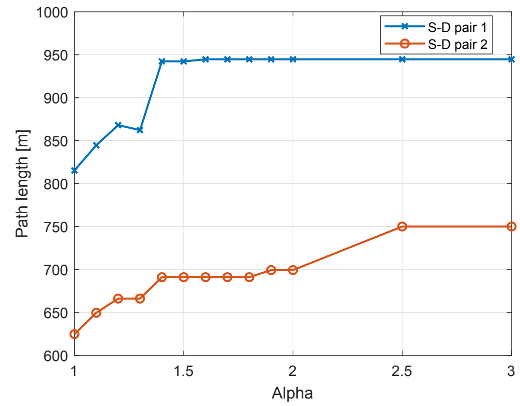


(a)

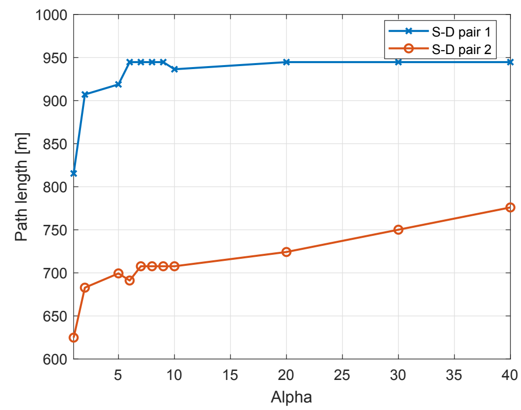


(b)

Figure 3: UAV trajectories for source-destination pair 2 with different biasing factor, (a) Modified Djikstra algorithm, (b) Modified A* algorithm.



(a)



(b)

Figure 4: Path lengths of UAV paths with different biasing factor α, (a) Modified Dijkstra algorithm, (b) Modified A* algorithm.

holes. The biased path finds the compromise between the two other paths, and follows a path longer than the shortest path but smaller than detour path and made a compromise at the quality of the link.

Similarly, Fig. 2(b) shows five different trajectories of UAV obtained with a modified A* algorithm for S-D pair 1. The shortest route i.e., a path with $\alpha = 1$ given by A* model is different from the shortest path acquired with the Dijkstra algorithm due to the heuristic approach used in A* search algorithm. Again, different values of α altered the course of UAV, and an optimal value of α can be used to meet the requirement of path length, QOR, and maximum QOD. Similarly, Fig. 3(a) and Fig. 3(b) illustrates different trajectories acquired with modified Dijkstra and A* algorithm, respectively, for source-destination pair 2. Interestingly in Fig. 3(a), it can be seen that in case of $\alpha = 2$, the proposed path is completely different from the naive shortest path and outage avoidance path, and by making smart moves the UAV did not take the longest route and also did not compromise much on the quality.

Now, it is interesting to analyze different metrics of paths that are acquired by different path planning approaches. The first metric considered here is the path length. Fig. 4(a) and Fig. 4(b) shows the length of the paths in meters, for both S-D pairs as a function of biasing factor α for modified Dijkstra and A* algorithm, respectively. It is critical to notice here that the modified Dijkstra approach is sensitive to even small values of the biasing factor. For S-D pairs 1 and 2, the path length already almost approaches to the maximum for α equals to 1.4 and 2.5, respectively. However, the modified A* algorithm is not that sensitive to the small changes in the biasing factor, as results with large values of biasing factor are shown in Fig. 4(b). The length of the detour path is not shown in Fig. 4 as that trajectory is obtained by considering $\alpha = \infty$. For S-D pair 1 with modified Dijkstra approach, length of the shortest path is 815 m for $\alpha = 1$, and the length of the longest path is 945 m for $\alpha = Infinity$, it means that the detour path is 15.9% extra long compared with the shortest path. Similarly, in the case of S-D pair 2, the length of the shortest path and complete outage avoidance path is 625 m and 776 m, respectively, which means fully outage avoidance path is 24.2% longer concerning the shortest path. Similarly, with a

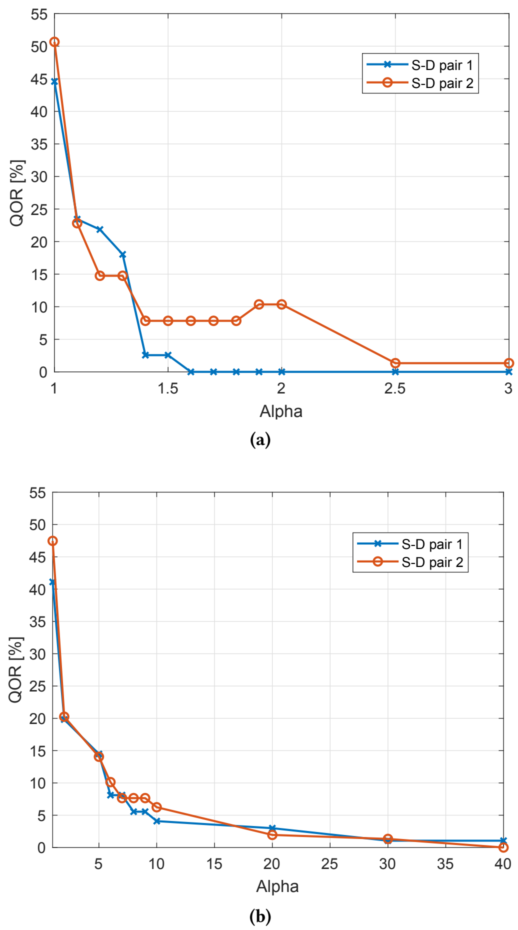


Figure 5: Quality outage ratio of UAV trajectories with different biasing factor α, (a) Modified Dijkstra algorithm, (b) Modified A* algorithm.

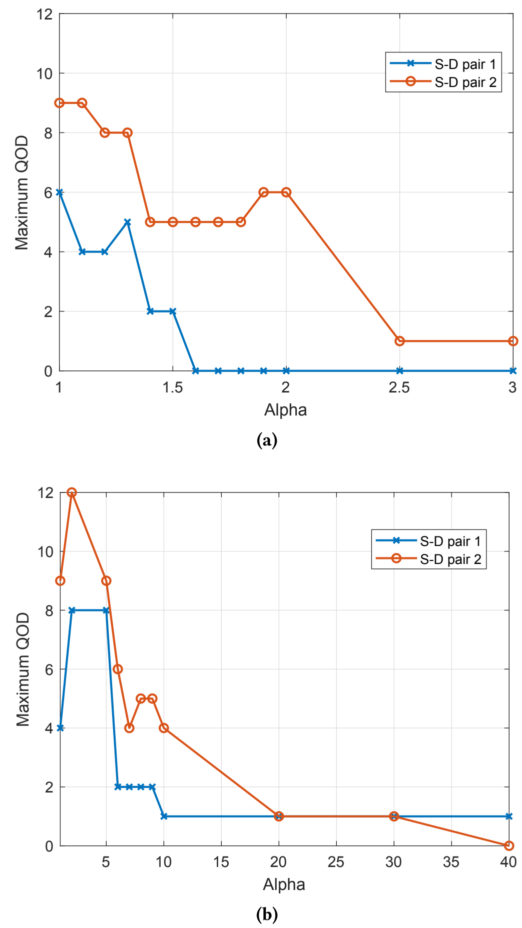


Figure 6: Maximum quality outage duration of UAV trajectories with different biasing factor α, (a) Modified Dijkstra algorithm, (b) Modified A* algorithm.

modified A* algorithm, different trajectories with different path lengths are achieved by changing the biasing factor alpha.

Fig. 5 shows the QOR against the biasing factor α. It can be deduced that generally by increasing the value of the biasing factor the QOR improves in both cases of modified Dijkstra and modified A* algorithm. It can also be seen that the trajectory with minimum path length has maximum QOR, and vice versa. The QOR of the outage avoidance path is zero, as it does not enter the coverage hole at all. By comparing Fig. 5(a) and Fig. 5(b) it can be seen that QOR changes gradually with the change in biasing factor in case of modified A* algorithm, the change in QOR is more abrupt in case of modified Dijkstra model. As mentioned before that although the path length of the shortest path found by the Dijkstra algorithm is the same as found by the A* algorithm, however, the trajectories were different. Therefore, the QOR for both the shortest path is also different. The QOR of the shortest path acquired by modified Dijkstra model for S-D pair 1 and 2 is 44.6% and 50.7%, respectively, and with modified A* algorithm for S-D pair 1 and 2 the QOR for the shortest path is 41.1% and 47.5%, respectively. Again, a compromise can be found between path length and QOR by adjusting the biasing factor according to the flight constraint.

Now, if we analyze Fig. 4(a) and Fig. 5(a) together, then we can see that for S-D pair 1, by using the biasing factor of 1.1 in modified Dijkstra model, the path length is increased by 3.6% and QOR is improved by 90.2% with respect to the shortest path, and for S-D pair 2 the change in path length is 3.8% and the improvement in QOR is 122%. Similarly, by analyzing Fig. 4(b) and Fig. 5(b) together we noticed that for S-D pair 1, by using the biasing factor of 2 in modified A* model, the path length is increased by 11.25% and QOR is improved by 108%, and for S-D pair 2 the path length is increased by 9.3% and the QOR is enhanced by 134%, in comparison with the naive shortest path. These numbers illustrate the effectiveness of adding a cellular aerial quality based biasing factor in modified Dijkstra and modified A* path search algorithms.

Finally, Fig. 6 shows the maximum QOD of trajectories for different values of the biasing factor. It is important to mention here that a single UAV trajectory might have several QODs, however, only maximum QOD of the UAV path is reported in Fig. 6. It was observed that the trend of maximum QOD is not linear with the biasing factor i.e., it may increase or decrease with the increase in biasing factor depending upon the aerial quality map. Maximum QOD along with path length and QOR puts a constraint While choosing the value of α. Lastly, the value of the biasing factor full filling all the flight constraints can be used to find the optimal trajectory of the UAV.

6 CONCLUSION

In this paper, we have proposed a modified form of Dijkstra and A* search algorithm for quality-aware trajectory planning of the UAV. The UAV trajectory/path was quantified and assessed in terms of three metrics known as path length, QOR, and maximum QoD. We have introduced a quality-aware biasing factor in our proposed model, which provides a trade-off between the path length and other quality metrics of the UAV trajectory. We have considered naive shortest path and complete quality outage avoidance path to compare them with our proposed pathfinding method. We analyzed two source-destination pairs in an area under consideration, and acquired simulation results revealed that the proposed approach significantly improves the QOR at the expense of a slight increase in path length compared with the naive shortest path. Simulation results show the improvement up to 134% in QOR with an increase of 9.3% path length compared with the shortest path. Our proposed approach found a compromise between the path length and other quality metrics of the UAV trajectory.

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