MEC-assisted Dynamic Geofencing for 5G-enabled UAV

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***Abstract*—5G-enabled UAV-based services have become popular for civilian applications. At the same time, certain no-fly zones will be highly dynamic, e.g. accident areas, large outdoor public events, VIP convoys etc. An appropriate geofencing algorithm is required to avoid the no-fly zone in such scenarios. However, it is challenging to execute a high computing process such as a geofencing algorithm for a resource constraint UAV. This paper proposes an architecture and a geofencing algorithm for 5G-enabled UAV using Mobile Edge Computing (MEC). Also, the 5G-enabled UAV must fly within the coverage area during a mission. Hence, there must be an optimal trade-off between 5G coverage and distance to travel to design a new trajectory for a 5G-enabled UAV. To this end, we propose a cost minimization problem to generate a new trajectory while a no-fly zone exists. Specifically, we design a cost function considering 5G coverage and the velocity of the UAV. Then, we propose a geofencing algorithm running at the MEC by adopting the fast marching method (FMM) to generate a new trajectory for the UAV. Finally, a numerical example shows how the proposed geofencing algorithm generates an optimal trajectory for a UAV to avoid a dynamically created no-fly zone while on the mission.**

***Index Terms*—Unmanned Aerial Vehicle (UAV), Mobile Edge Computing (MEC), 5G, Fast Marching Method (FMM), Geofence**

I. Introduction

The recent upsurge in UAV draws attention to next-generation communication networks such as 5G [1]. It is proven that UAV have immense potential for several civilian use cases such as extending network coverage [2], logistic delivery [3], fire fighting [4], crowd surveillance [5], and many more. The primary challenges to using a UAV for serving such use cases are limited on-board computational capability and limited flight time of the UAVs. Additionally, there is a requirement of a high data rate to transfer the mission-driven data from UAV to the ground control center. A UAV can offload high computational processes to remote computers thanks to ultra-reliable low-latency communication of 5G and MEC. On the other hand, there is a requirement that a UAV must have the ability to avoid a no-fly zone while deployed for a mission to increase safety and reliability. In this work, we propose a geofencing algorithm adopting FMM running at the edge computer to generate a new trajectory for the UAV to avoid a dynamically created no-fly zone during the mission.

We consider an urban scenario where a 5G-enabled UAV is deployed for different applications such as logistic delivery, extending network coverage, etc. Once there is a requirement to deploy a UAV for a specific application, the UAV operator uploads a pre-defined trajectory for the mission to the UAV to reach the target location safely. There will be no-fly zone due to air convoy, fire, or public events. Therefore, a UAV requires the ability to avoid the no-fly zone in real-time. Typically, the solution to a trajectory planning attempts to create a costmap (dividing the map into grids and assigning a cost to the action of moving between contiguous cells) of a region of interest (RoI) and minimizes the cost to generate the optimal trajectory [6]–[10]. However, in large scale scenarios, this process requires a high computational processor to produce an optimal trajectory in less time. On the other hand, a UAV has limited resources and energy to execute high computational processes such as executing a geofencing algorithm and generating a new route to avoid the no-fly zone. Hence, we offload the process to MEC to execute the geofencing algorithm in real-time and send the new trajectory to the UAV to avoid a no-fly zone over the 5G network. This article narrates the optimal trajectory planning at the presence of a dynamically created no-fly zone during the mission.

Several works exist to solve the trajectory optimization problem in the literature [6]–[11]. In this work, we propose a geofencing algorithm based on the FMM [12]. It is already proven in the literature that FMM is useful for trajectory planning, obstacle avoidance, and generating smooth and short trajectory curves [13]. The primary objective of this work is to design the trajectory using the proposed geofencing algorithm so that the UAV flies within the coverage area of the 5G networks. The FMM helps to consider this constraint as the path is not restricted within the grid cells and the wave propagates using the costmap to generate the new smooth trajectory. The novelty of this work is to design an appropriate cost function and costmap considering the 5G network coverage and restricted flight time of a UAV. Additionally, the proposed solution aims to optimize the trade-off between 5G network coverage and distance to travel by the UAV while generating the new trajectory.

II. Related Work

Gurriet *et al.* [6] proposed an obstacle avoidance-based fencing technique to avoid the obstacle for UAVs. In this work, they assumed the UAV aware of the situation of the environment. On top of this assumption, they designed an obstacle avoidance algorithm exploring quadratic programming. Stevens *et al.* [7] proposed a Triangle Weight Characterization with Adjacency (TWCA) algorithm to identify whether a UAV

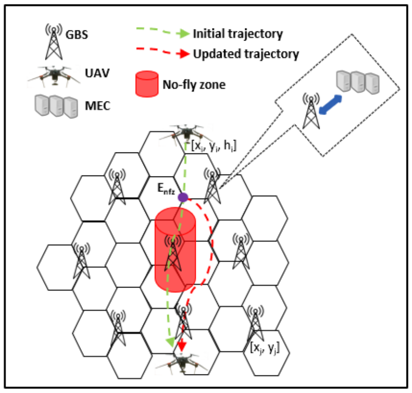

Fig. 1: Network Architecture and Problem Scenario

violates the geofence boundary. The authors defined keep-in and keep-out categories to identify the geofence boundary violation for each UAV. The authors explored the point-in-polygon problem in this proposed work to achieve the goal. Dinh *et al.* [8] attempted to design a control software to control multiple UAVs. Specifically, the designed software was produced to maintain safe distance for collision avoidance and geofencing for multiple UAVs. The authors explored linear programming to design the software. Fu *et al.* [9] proposed a geofence algorithm to geofencing violation and avoidance technique for an unmanned aircraft system (UAS). The authors designed a pre-control layer to scale the original geofence in this work. Next, they proposed an improved ray method algorithm to detect the geofence violation and re-plan the route of the UAS. The authors in [10] proposed an explicit reference governor-based (ERG) framework for constrained geofencing applications. In this work, the authors focused on the control of the UAVs to avoid walls and objects.

III. Problem Formulation and Solution Approach

A. System Model

We consider a single UAV i and N ground base stations (GBS) are distributed according to the guidelines defined by the report of ITU-R M.[IMT-2020.EVAL] [14] for 5G urban environment, as described in Figure 1. All the GBSs are assumed to transmit mmWave frequency band with transmitting power P_j. We assume that the UAV fly at a constant height $h_{min} \leq h_i \leq h_{max}$ to avoid obstacle such as high rise building in an urban area. The 2D location of each GBS is represented as $\omega_j = [x_j, y_j]$ and the height of remote radio head (RRH) of each GBS is $h_B < h_i$. On the other hand, $\omega_i = [x_i, y_i, h_i]$ represents the 3D coordinate of the UAV i. We assume that each GBS is equipped with the processing ability to facilitate the UAV with mobile edge computing (MEC).

B. UAV-GBS Comunication Model

We consider the probabilistic line-of-sight (LoS) and non-LoS (NLoS) model link between a UAV and GBS.

The path-loss for LoS and NLoS links between a UAV i and GBS j are expressed as [2]:

$$PL_{ij}^{LoS} = 20\log(4\pi f d_{ji}/c) + \eta_{LoS},$$
$$PL_{ij}^{NLoS} = 20\log(4\pi f d_{ji}/c) + \eta_{NLoS}, \quad (1)$$

where d_{ji} denotes the distance between UAV i and GBS j and is expressed as $d_{ji} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2 + (h_B - h_i)^2}$, c represents the speed of light, f denotes the carrier frequency, and η_{LoS} and η_{NLoS} denote the attenuation factors of LoS and NLoS links, respectively. Further, the probability of LoS link between UAV i and GBS j is described as [2]:

$$Pr_{ij}^{LoS} = \left(1 + a exp(-b[\theta_{ij} - a])\right)^{-1}, \quad (2)$$

where $\theta_{ij} = \sin^{-1}[(h_i - h_B)/d_{ji}]$ denotes the elevation angle between UAV i and GBS j, a and b are the constants of the environment. Therefore, $Pr_{ji}^{NLoS} = 1 - Pr_{ij}^{LoS}$. Also, the average path loss between UAV i and GBS j is expressed using Equation (1) and (2) as $PL_{ij} = (PL_{ij}^{LoS} Pr_{ij}^{LoS}) + (PL_{ij}^{NLoS} Pr_{ij}^{NLoS})$. As described in [15], the signal-to-interference-plus-noise-ratio (SINR) for UAV i and GBS j is expressed as:

$$\psi_{ij} = \frac{P_j G_{ij}}{\sum_{q=1, q\neq j}^{N} P_q(t) G_{iq}(t) + \sigma^2}, \quad (3)$$

where $G_{ij}(t) = 1/\overline{PL}_{ij}$ denotes the channel gain between UAV i and GBS j and σ^2 defines the mean of Gaussian noise. The SINR is one of the important parameter of this work because it helps to generate the costmap for trajectory generation.

C. Problem Overview

In this section, we describe the overview of the problem scenario. We assume that a UAV is deployed to accomplish a mission for a specific application in an urban area. Therefore, the UAV operator uploads a pre-defined trajectory to the UAV to reach the target location considering the 5G coverage and less travelled distance. The green line in Figure 1 indicates the initial trajectory of the UAV. However, a no-fly zone is created for the deployed UAV due to public events, air-convoy, or any emergency while on mission. At the same time, the UAV reaches the location E_{nfz} (see Figure 1) during the mission. We consider a no-fly zone as a shape of a cylinder (see Figure 1) with radius R_{nfz} and infinite length to ensure that the UAV can not invade the no-fly zone. Therefore, the MEC executes a geofencing algorithm to identify the optimal trajectory for the UAV to avoid the no-fly zone considering the velocity (or distance to travel) of the UAV and 5G network coverage in real-time. Once the new trajectory is generated at MEC, a new trajectory is transmitted to the UAV to avoid the no-fly zone through the 5G network. The red line in Figure 1 denotes the updated trajectory of the UAV. We create a cost function that considers 5G coverage and distance as primary parameters to generate an optimal trajectory. Next, we create the costmap of the region. Finally, we minimize the total cost to generate the new trajectory.

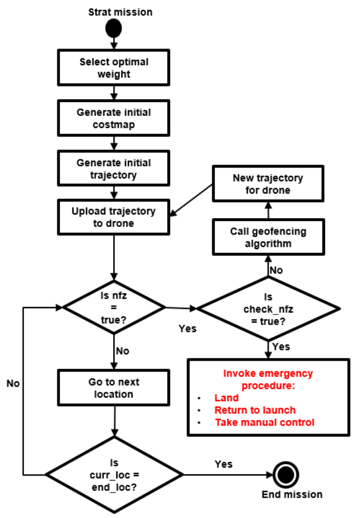

Fig. 2: Solution Work Flow

D. Cost Function

This section describes the minimization of the accumulated costs or costmap to generate the new trajectory. We assume that the RoI is divided into a grid-like structure, and each grid cell is associated with a cost. We assume that the initial trajectory is optimized before deploying the UAV for the mission. This paper aims to minimize the associated cost to generate a new trajectory considering the 5G network coverage and distance to travel to avoid a no-fly zone. We define the cost of each cell, C_i, as:

$$C_i = \frac{1}{v_{avg}} + \frac{[\psi_{max} - \psi_{min}]}{[\psi_{max} - \psi_{ij}]w} = \frac{1}{v_{avg}} + \frac{\alpha}{w}, \tag{4}$$

where $v_{avg} > 0$ denotes the average speed of the UAV, $\alpha = [\psi_{max} - \psi_{min}]/[\psi_{max} - \psi_{ij}]$, ψ_{max} and ψ_{min} represent the upper and lower bound of the SINR, w indicates the weight factor, and $1 \geq w > 0$. Therefore, the objective of this work is to minimize the total accumulated cost in order to generate the new trajectory to avoid the no-fly zone. Hence, we can write the objective as:

$$\underset{\omega_i, \psi_{ij}}{\text{minimize}} \int_S C_i ds \tag{5}$$

$$\text{subject to} \quad \psi_{min} \leq \psi_{ij} \leq \psi_{max}, \tag{6}$$

$$(x_i - x_{nfz})^2 + (y_i - y_{nfz})^2 \geq R_{nfz}, \tag{7}$$

where S defines the path length. The constraint in Equation (6) ensures that the UAV remains within the 5G coverage. On the other hand, the constraint in Equation (7) restricts the UAV to enter no-fly zone.

IV. Solution Approach and Results

The proposed solution approach comprises two contributors — a) solution manager, and b) tracker. Typically, the MEC performs the role of solution manager, and the UAV acts as a tracker in this context. We describe the role of each contributor in the following section. Finally, we discuss the solution flow and the result of the proposed scheme in this section, as described in Figure 2.

Algorithm 1 Algorithm for Generating Costmap

INPUTS:
Area of interest
R_{nfz}, if no-fly zone occurs
Centroid location of no-fly zone, if no-fly zone exists
OUTPUT:
C
PROCEDURE:
for all the location in the RoI **do**
  if nofly-zone exists and the location is in no-fly zone **then**
    assign a high cost to the location in costmap C
  else if the SINR is less than the threshold **then**
    assign a high cost to the location in costmap C
  else
    assign the cost value using Equation (4) to the location in costmap C
  end if
end for
return C

A. Solution Manager Description

The role of the solution manager is to generate the costmap, optimal trajectory, and control the mission in real-time for the UAV. There are two modules to help the solution manager to create costmap and optimal trajectory. These modules are known as — a) costmap generator, and b) trajectory generator.

1) Costmap Generator: The costmap generator directs the scenario as a 2D costmap C considering 5G network coverage, velocity of the UAV (as described in Equation (4)) and no-fly zone if it occurs. In this paper, the costmap generator considers the 2D costmap as we assume that the UAV flies to a constant altitude (as described in Section III-A). The role of the costmap generator is to assign a cost to the different cells and to identify the traversable and non-traversable areas and include them in costmap C. To simplify the scenario, it considers the no-fly zone (if it exists), stated in Equation 7, and the area with less coverage, stated in Equation (6), as the non-traversable area to create the costmap C. Once the costmap generator generates or updates the costmap C of the RoI, the solution manager invokes the trajectory generator to generate the new trajectory for the UAV. Algorithm 1 describes the process of generating the costmap. Algorithm 1 considers the RoI, the center of the no-fly zone (if it exists), and the radius of the no-fly zone (if it exists) as inputs. Thereafter, it checks if the no-fly zone exists and the location is inside the no-fly zone, then it assigns a pre-defined high cost to the location in the costmap. Next, it checks whether the SINR applying Equation (3) is greater than the threshold or not. If the SINR is lower than the threshold, it assigns the pre-defined high cost to the location in the costmap. Otherwise, it assigns the cost for the location using the Equation (4) in the costmap. Basically, Algorithm 1 considers the Equation (7) while assigning the costs for no-fly zone, if exists, to the costmap. We consider a 2D matrix to store the cost of each cell of the grid for RoI. Therefore, the time complexity of Algorithm 1 is $O(n^2)$.

2) Trajectory Generator: Once the costmap generator generates or updates the costmap of the RoI, the solution manager invokes the trajectory generator to generate the optimal tra-

Algorithm 2 Geofencing Algorithm

INPUTS:
1: E_{nfz}
2: R_{nfz}
3: $[x_{nfz}, y_{nfz}]$ ▷ Location of center of no-fly zone
4: L_{end} ▷ target location of the mission
5: C
6: $\mathbb{C}$ ▷ pre-defined high cost

OUTPUT:
1: G ▷ a list containing new trajectory

PROCEDURE:
1: Initialize: $C^{'} = C$, $s = E_{nfz}$, $e = L_{end}$
2: **for all** $C^{'}[i][j]$ **do** ▷ i, j are the index and represents respective x, y position
3: **if** $(x_i - x_{nfz})^2 + (y_i - y_{nfz})^2 \leq R_{nfz}$ **then**
4: $C[i][j] = \mathbb{C}$
5: **end if**
6: **end for**
7: Call FMM [12] considering $s, e, C^{'}$
8: Save the new trajectory to G
9: **return** G

jectory using the costmap. The trajectory generator considers start location, target location, and the costmap as an input. Then, it invokes FMM [12] to generate the optimal trajectory for the UAV. FMM, a widely used in path planning [13], is a numerical method [12] for modelling wavefront propagation by solving the Eikonal differential equation:

$$|\nabla u(x)| = \frac{1}{f(x)} \tag{8}$$

where x refers to a position, u is the function of the arrival time of the wave, and f is the speed of the wave to the normal direction to position x. FMM generates the minimum length path between any starting point to any target point in an RoI exploring the traversable area [12]. To generate the optimal trajectory, we consider the costmap as described in Section IV-A1. The arrival time of each location on the costmap is calculated by simulating a wave starting from the initial point. Then, the gradient descent helps to generate the optimal path by backtracking the minimum arrival time from the target location to the start location [12], [13]. Additionally, the time complexity of FMM is $O(n \log n)$ [12].

B. Tracker

The UAV acts as a tracker. Once the solution manager generates the optimal trajectory for the UAV, the new or updated trajectory is uploaded to the UAV. Then, the UAV tracks the trajectory. However, it continuously checks if there is a new no-fly zone or not. If yes, it sends the information about the end of the mission to the solution manager through 5G communication infrastructure.

C. Geofencing Algorithm

Algorithm 2 describes the proposed geofencing algorithm. This algorithm considers UAV's current position, target location, initial costmap (C), the radius of the no-fly zone, centroid location of the no-fly zone, and a pre-defined high cost as input. Next, it initializes UAV's current position as the start location $s = E_{nfz}$, target location as end location e, and $C^{'} = C$. Then, it assigns high costs to the locations inside the no-fly zone in $C^{'}$ and creates a new updated costmap $C^{'}$. Finally, it calls the FMM to generate the new path considering s, e, and $C^{'}$ as input parameters. The time complexity of Step 2-5 of Algorithm 2 is $O(n^2)$.

TABLE I: Simulation Parameters

Parameters	Values
Simulation area	$500 \times 500\ m^2$
η	100 [16]
P_j	44 dBm [17]
σ^2	-95 dBm [2]
f_c	4 GHz [14]
v_{avg}	5 m/s
a	10.39 [15]
b	0.05 [15]
h_B	50 m
h_i	60 m

D. Solution Flow

In this section, we describe the solution flow of the proposed scheme, as shown in Figure 2. The solution manager plays an active part in the solution flow. As described in Figure 2, the solution manager selects the optimal weight for the entire mission considering the intervention from the UAV operators. This selection is crucial as the weight in Equation (4) defines how much weight for network coverage should be considered during the mission. The solution manager analyzes the mean deviation regarding distance from the optimal path (a straight line between start and target location of the mission) using different weights and asks UAV operators to select the optimal choice based on the allowable deviated distance and flight time of the UAV. Once the weight is chosen for the entire mission, the solution manager invokes the costmap generator to generate the costmap using Algorithm 1. Then, the trajectory generator generates the initial trajectory of the mission. Next, the solution manager uploads the mission trajectory to the UAV. Thereafter, the UAV starts to follow the waypoints to complete the mission. However, it continuously checks whether the next location is the end location or not. If yes, the UAV sends the information about the end of the mission to the solution manager. On the other hand, the solution manager continuously checks if a no-fly zone occurs or not during the entire mission. If the no-fly zone is created, then it checks if the UAV is already inside the no-fly zone or not (see Figure 2). It is possible because the UAV continuously sends all the information regarding its current statuses, such as position, energy, even real-time image or video feed based on the application through 5G communication. Suppose, the UAV is inside the no-fly zone. In that case, it invokes emergency procedure and sends the instruction to the UAV such as land, return to launch, or manual control according to the situation (see Figure 2). Otherwise, it calls the geofencing algorithm (Algorithm 2) to generate a new trajectory for the UAV to avoid a no-fly zone in real-time. Once the new path is generated, the solution manager uploads the updated trajectory to the UAV to avoid the no-fly zone.

Fig. 3: Simulation Area around SnT, Kirchberg Campus, University of Luxembourg

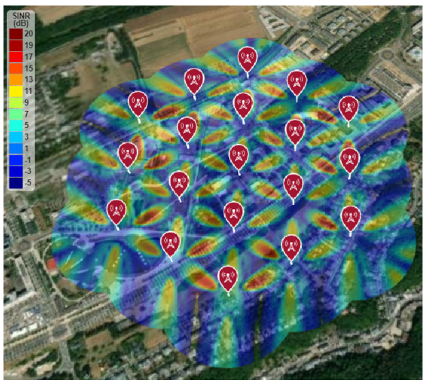

Fig. 4: SINR Map around SnT, Kirchberg Campus, University of Luxembourg

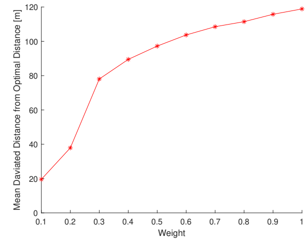

Fig. 5: Deviated Distance from Optimal Path vs Weight

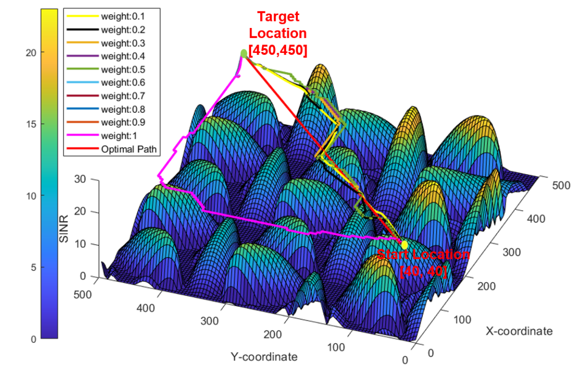

Fig. 6: An Instance of Trajectories for Different Weights

E. Results and Discussion

1) Simulation Parameter: We consider $500 \times 500\ m^2$ area around SnT, Kirchberg campus of University of Luxembourg as shown in Figure 3. Table I refers the simulation parameters that we consider for the simulation. We consider the location A (see Figure 3) as the origin for the simulation, i.e., the local coordinate of A is $(0, 0)$. However, the global coordinate of A is $(49.624406, 6.153392)$. We consider the (north, east, up) method to convert the global coordinate to the local Cartesian coordinate system with respect to the origin A. Additionally, we create $5 \times 5\ m^2$ grids for the simulation area to generate the costmap. Therefore, we refer to each location as a cell of the grid and assume that all the points within the grid have equal SINR values. Next, we create transmission sites (GBSs) according to the report of ITU-R M.[IMT-2020.EVAL] [14] [18] for 5G urban environment around the SnT, Kirchberg campus of University of Luxembourg. Figure 4 shows the SINR map of the simulated area.

2) Optimal Weight Selection: Figure 5 shows the mean deviated distances from the optimal path while considering ten different weights. As stated in Section IV-D, the optimal path or distance between a start and target location is the straight-line, considering that UAV flies to a constant altitude. We conduct 1000 iterations to generate the result as shown in Figure 5. For each iteration, we select random start and target location. Then, we call FMM [12] to generate the optimal path for each weight using the available costmap of the RoI. Next, we store the mean deviation in the distance for each path from the optimal path for each iteration. Finally, we generate the mean deviation from the optimal path in the distance for each weight, as shown in Figure 5. The result in Figure 5 describes that mean deviated distance is increased while increasing the weight for network coverage in Equation (4). The reason is obvious because the generated path attempts to cover the higher network coverage area while increasing the weights. As a result, the distance to travel is increased. Therefore, the UAV operators decide how much weight should be considered for the entire mission considering the network coverage and distance to travel. Figure 6 describes an instance where the start location of a mission is $[40, 40]$, target location is $[450, 450]$, and the generated path for different weights of the network coverage. In the subsequent section, we continue this example with the initial trajectory and the trajectory generated by the solution manager when a no-fly zone occurs during the mission.

3) Numerical Example of Proposed Solution: As discussed in the previous section, let us consider that the start location and target location for a specific mission are $[40, 40]$ and $[450, 450]$. As stated in Figure 2, the solution manager calls the optimal weight selection module to select the weight for the network coverage to generate the trajectory for the mission. For instance, the network operator decides that the maximum allowable deviation from the optimal solution is 50 m. Therefore, the optimal weight for this example case

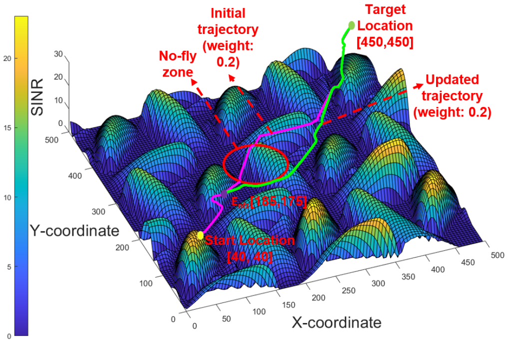

Fig. 7: Example of Proposed Solution

is 0.2, as described in Figure 5. Next, the solution manager invokes costmap generator to generate the costmap of the RoI using the optimal weight, i.e., 0.2 as described in Section IV-A1. Once the costmap is generated, the trajectory generator generates the initial trajectory for the UAV, as shown in Figure 7 (magenta line). Therefore, the mission trajectory is uploaded in the UAV, and the UAV starts to follow the trajectory accordingly. Meanwhile, the UAV reaches the location E_{nfz} ($[112.76, 124.24, 60]$), a no-fly zone is created due to a public event or air convoy. We randomly select the E_{nfz} from the current trajectory of the UAV for the simulation. The center of the no-fly and the radius are considered for this example case as $[185, 175]$ and $R_{nfz} = 50$, respectively, to demonstrate the applicability of the geofencing algorithm (see Figure 7). Once there is a no-fly zone created, the check parameter for the no-fly zone is true (see Figure 2). Accordingly, the solution manager checks whether the UAV is already inside the no-fly zone or not. In this example, the current position of UAV (E_{nfz}) is outside of the no-fly zone, as shown in Figure 7. Therefore, the solution manager calls the geofence algorithm (Algorithm 2) to generate a new trajectory for the UAV to avoid the no-fly zone. In this example, the input parameters for the Algorithm 2 are $E_{nfz} = [112.76, 124.24]$, $R_{nfz} = 50$ m, center of no-fly zone ($[185, 175]$), $L_{end} = [450, 450]$, initial costmap generated by costmap generator (C), and $\mathbb{C} = 30$ dB. Finally, the Algorithm 2 generates the new trajectory as shown in Figure 7 (green line) to avoid the no-fly zone.

V. Conclusion

In this paper, we proposed an architecture combining MEC, 5G network infrastructure, and a UAV to envision the solution for UAV-aided real-life applications. Then, we demonstrated how a UAV deals with dynamically created geofence with the help of next-generation communication technology such as 5G and MEC. We formulated a cost minimization problem to generate an optimal path in the presence of a no-fly zone. To solve the problem, we demonstrated the solution with a solution flow. Specifically, we proposed a cost function considering the 5G network coverage and the velocity of the UAV. Next, we proposed Algorithm 1 to generate an efficient costmap using the proposed cost function. Then, we introduced Algorithm 2 adopting FMM to generate a new trajectory of the UAV to avoid the no-fly zone. Finally, a numerical illustrating example showed that the proposed geofencing algorithm efficiently created a new trajectory for the UAV to avoid a no-fly zone. In the future, we extend this work to analyze the system's efficiency in terms of delay, throughput, and computation considering the 5G network and MEC, respectively. Additionally, we intend to implement the proposed algorithm in a real test-bed.

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