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Multi-UAV Navigation for Optimized Video Surveillance of Ground Vehicles on Uneven Terrains

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***Abstract*—This paper addresses a trajectory planning problem for a team of UAVs following several ground vehicles on uneven terrain for video surveillance. A model predictive control-based multi-UAV path planning algorithm is designed. A theoretical justification of the path planning algorithm is provided. Extensive simulation studies demonstrate the performance of the proposed method.**

***Index Terms*—Unmanned aerial vehicles, drones, ground traffic monitoring, multi-UAV navigation, path planning, guidance, video surveillance, uneven terrains, ground vehicles, optimal 3D UAV navigation.**

I. Introduction

Teams of unmanned aerial vehicles (UAVs) attracted a lot of interest from both industry and academia in recent years. UAVs have been successfully used in many defence and commercial applications. These applications include but not limited to cellular communication networks, wireless sensor networks, environmental monitoring, mobile edge computing, emergency communications, military activities, rescue and protection missions, target tracking, last-mile delivery, eavesdropping and counter-eavesdropping; see e.g. [1]–[8] and references therein. A challenging field for applications of UAV teams is the surveillance of ground targets, consisting of various problems of ground traffic surveillance, wildlife monitoring, monitoring of agricultural fields, livestock surveillance, disaster areas surveillance, and target surveillance for policing and military purposes [9]–[16]. In these monitoring tasks, a common scenario involves a team of UAVs with video cameras monitoring several moving ground targets. A typical requirement of such video surveillance problems is to guarantee that all targets of interest or all points of the monitored terrain area are observed by, at least, one UAV often enough. A challenging generalization of such a requirement is a situation in which UAVs are navigated over uneven terrains. Such uneven terrains are ground areas which are impossible to model with sufficient precision by a perfect plane. In such situations, the line of sight (LoS) of video cameras mounted on UAVs is often occluded by some points of the terrain. Complex uneven terrains are especially widespread in urban environments containing numerous tall buildings and narrow roads [14], [17]. It is expected that such scenarios will become especially relevant due to the growing production of relatively tiny UAVs operating at low altitudes [14].

There exist numerous recent publications that study various problems of UAV surveillance of ground targets and areas. The papers [11] and [13] propose various UAV video surveillance strategies that are based on Voronoi partitioning groups of moving cars or pedestrians and navigating UAVs towards centres of Voronoi cells. Fast path planning schemes for a single UAV tracking targets were proposed in [18], [19]. In [20], the problem of monitoring frontiers of quickly spreading environmental disaster areas by a UAV team was studied. The paper [21] proposes a path planning algorithm for aerial surveillance that is based on a rapidly exploring random tree approach. The publication [12] develops a multi-UAV navigation algorithm for coordinated standoff tracking of moving target groups. The paper [22] discusses the monitoring of suspicious mobile targets using solar-powered fixed-wing UAVs. All these publications do not properly address the issue of uneven terrains where the LoS between a UAV and a target is often occluded by some walls, buildings, hills etc.

The current paper addresses the problem of video monitoring several ground vehicles moving on uneven terrain by a team of UAVs. The goal of the UAV team is to observe the ground vehicles by keeping LoS between the UAVs and the vehicles for as long as possible. Moreover, the UAVs are navigated to keep distances to the ground vehicle as short as possible to improve the quality of video surveillance. We propose an effective navigation algorithm that maximizes some objective function that takes into account both the time during which LoS between the UAVs and the ground vehicles are not occluded by the uneven terrain and the distances between UAVs and vehicles that are seen from these UAVs. The main contributions are summarized as follows. 1) The developed navigation framework fully addresses the issue of non-flat ground which may often block the LoS and make video surveillance impossible. We do not know other publications in the area fully addressing this important issue. 2) The proposed navigation method uses the model predictive control (MPC) framework [23] and constructs an almost optimal multi-UAV trajectory, in the sense, that when some parameters of the algorithm tend to infinity, the built trajectory asymptotically converges to the optimum. 3) The proposed UAV navigation scheme guarantees collision avoidance, i.e. the distance between any two of the UAVs is never less than some given safety distance.

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II. Investigated Problem

We study a multi-UAV team containing UAVs labelled $i = 1, \dots, K$, where $K > 1$. Let $(x_i(t), y_i(t), z_i(t))$ be the 3D position of UAV i. We concentrate on the following very common model of the motion of UAV i:

$$\begin{cases} \dot{x}_i(t) = v_i(t)\cos(\lambda_i(t)), \\ \dot{y}_i(t) = v_i(t)\sin(\lambda_i(t)), \\ \dot{\lambda}_i(t) = \omega_i(t), \\ \dot{z}_i(t) = u_i(t), \end{cases} \tag{1}$$

where $\lambda_i(\cdot)$ is the axis angle of UAV i in the horizontal plane; $v_i(\cdot)$, $\omega_i(\cdot)$ and $u_i(\cdot)$ are control inputs of controlled plant (1), that belong to the intervals $0 \le v_i(\cdot) \le \Delta_1$, $|\omega_i(\cdot)| \le \Delta_2$, and $|u_i(\cdot)| \le \Delta_3$ with some given upper limits Δ_1, Δ_2 and Δ_3. Also, the following inequalities for the altitude $z_i(t)$ of UAV i must always hold:

$$Z^{min} \le z_i(t) \le Z^{max}, \tag{2}$$

where $0 < Z^{min} < Z^{max}$ are given constants. Furthermore, to avoid collisions between each other, any two UAVs i and h ($i \neq h$) must keep at least a safe distance δ_s away from each other at any time:

$$\sqrt{(x_i - x_h)^2 + (y_i - y_h)^2 + (z_i - z_h)^2} \ge \delta_s, \tag{3}$$

where $\delta_s > 0$ is a given constant.

The UAVs fly over an uneven terrain modelled by a given function $p(x, y)$ such that $(x, y, p(x, y)$ is a 3D position of a point on the terrain. Notice that we consider a very general case where the UAVs can fly at a lower altitude than the terrains [24]. To avoid the problem of avoiding collision with high segments of the ground, which is indeed a well-known problem, we introduce the following obstacle avoidance requirement:

$$z_i(t) > p(x_i(t), y_i(t)) + s_m \quad \forall i, t, \tag{4}$$

where the safety margin $s_m > 0$ is given. It is obvious that if (4) holds, then the UAVs cannot collude with the ground. We also have L ground vehicles, indexed $j = 1, \dots, L$, that are moving on the non-even terrain along some network of roads. The goal of the UAVs is to monitor these ground vehicles. Each UAV has a video camera pointed to the ground with the visibility sector $\alpha \in (0, \pi)$, see Fig. 1. A vehicle at the terrain location (x, y, z) is seen from UAV i with coordinates (x_i, y_i, z_i), if the following two conditions hold:

1) The vehicle is inside the UAV's visibility cone, i.e.,

$$\sqrt{(x_i - x)^2 + (y_i - y)^2} \le (z_i - z)\tan\left(\frac{\alpha}{2}\right); \tag{5}$$

2) LoS from the point (x_i, y_i, z_i) to the point (x, y, z) is not occluded by some terrain part, see Fig. 1.

Available information: There is some communication between the UAVs, so any UAV receives positions and headings of other UAVs. Moreover, each UAV gets the coordinates and velocities of all ground vehicles that are visible to other UAVs. Furthermore, each UAV knows the altitude function $a(x, y)$ and the coordinates of the network of roads. Then control inputs for all UAVs are calculated at one of the UAVs and communicated to other UAVs.

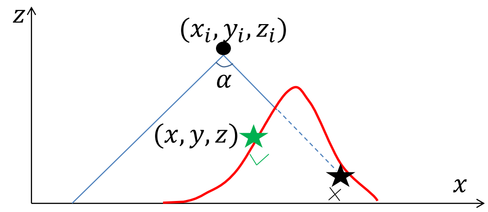


Fig. 1: The vision cone of a UAV.

The objective of the UAV team is to navigate itself so that all ground vehicles are visible from the UAVs as much as possible.

Let $T > 0$ be a given time. First, we state a problem for the time interval $[t_0, t_0 + T]$. One assumption is that the UAVs know the positions and the velocities of all ground vehicles at $t = t_0$. As we assume that there is some communication between the UAVs so that each UAV gets the coordinates and velocities of all ground vehicles that are visible by other UAVs, this assumption obviously holds if each ground vehicle is visible by at least one UAV at $t = t_0$ which is quite typical for realistic scenarios. Then the target speed can be estimated from its coordinates. Notice that assumptions of this type are common in problems of aerial ground target surveillance, see e.g. [9], [10].

Moreover, we assume that all vehicles will move with the same speeds over time interval $[t_0, t_0 + T]$. As the vehicles move along some road networks, for each vehicle j there exist $n_j \ge 1$ its possible trajectories over $[t_0, t_0 + T]$, and all those trajectories are known to the UAVs; see Fig. 2. Let $v(t) := (v_1(t), \dots, v_K(t)), \omega(t) := (\omega_1(t), \dots, \omega_K(t)), u(t) := (u_1(t), \dots, u_K(t))$ be the vectors of control inputs of the system of K UAVs described by (1). Any trajectory of the system (1) is defined by initial conditions $(x_i(t_0), y_i(t_0), z_i(t_0)), i = 1, \dots, K$ and control inputs $v(\cdot), \omega(\cdot), u(\cdot)$. We assume that initial conditions $z_i(t_0)$ satisfy the constraints (2), (3) and (4). Introduce the functions $L_j(t, v(\cdot), \omega(\cdot), u(\cdot)), j = 1, \dots, M$ as follows: $L_j(t, v(\cdot), \omega(\cdot), u(\cdot)) := 1$ if vehicle j at time t is seen from at least one UAV, $L_j(t, v(\cdot), \omega(\cdot), u(\cdot)) := 0$ otherwise. Moreover, define the functions $L_{ij}(t, v(\cdot), \omega(\cdot), u(\cdot)), i = 1, \dots, K, \ j = 1, \dots, M$ by $L_{ij}(t, v(\cdot), \omega(\cdot), u(\cdot)) := 1$ if vehicle j at time t is seen from UAV i, $L_{ij}(t, v(\cdot), \omega(\cdot), u(\cdot)) := 0$ otherwise.

Let $\beta > 0$ be a given constant. Now, we can introduce the following optimal control problem:

$$\begin{aligned} \mathcal{L}(v(\cdot), \omega(\cdot), u(\cdot)) := \min_{j=1,\dots,L} \int_{t_0}^{t_0+T} L_j(t, v(\cdot), \omega(\cdot), u(\cdot))dt \\ + \beta \sum_{j=1}^{L}\sum_{i=1}^{K} \int_{t_0}^{t_0+T} L_{ij}(t, v(\cdot), \omega(\cdot), u(\cdot))dt \\ \mathcal{L}(v(\cdot), \omega(\cdot), u(\cdot)) \to \sup, \end{aligned} \tag{6}$$

where the supremum is taken over all possible UAV control inputs $v(\cdot), \omega(\cdot), u(\cdot)$. It is obvious that the first integral in (6) describes the time during which vehicle j is seen from at least one UAV. The second term describes the sum of the lengths of all time intervals during which some ground vehicle is seen from some UAV. So in the optimization problem (6), the objective function can be viewed as a measure of the quality of monitoring L vehicles by the UAV team.

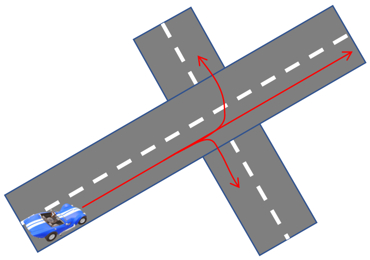


Fig. 2: Possible trajectories of vehicle j when it moves along some road networks.

Definition II.1. *A trajectory of the system (1) is called* ***high*** *if for any i, $u_i(t) = U^{max}$ if $z_i(t) < Z^{max}$, and $u_i(t) = 0$ if $z_i(t) = Z^{max}$.*

It is clear that a high trajectory always tends to Z^{max} with the maximum allowed vertical speed and after it reaches Z^{max}, it always satisfies the constraint $z_i(t) = Z^{max}$.

Proposition II.1. *For any trajectory of the system (1) defined by some initial conditions and control inputs $v(\cdot), \omega(\cdot), u(\cdot)$, there exists a high trajectory defined by the same initial conditions and some control inputs $v^*(\cdot), \omega^*(\cdot), u^*(\cdot)$ such that $\mathcal{L}(v^*(\cdot), \omega^*(\cdot), u^*(\cdot)) \geq \mathcal{L}(v(\cdot), \omega(\cdot), u(\cdot))$.*

Proof. Indeed, for a given trajectory with control inputs $v(\cdot), \omega(\cdot), u(\cdot)$, we introduce another trajectory defined by the same initial conditions and the control inputs $u_i^*(t) = U^{max}$ if $z_i(t) < Z^{max}$, and $u_i^*(t) = 0$ if $z_i(t) = Z^{max}$, $\omega^*(\cdot) = \omega(\cdot)$ and $u^*(\cdot) = u(\cdot)$. It is obvious that this new trajectory is high. Moreover, the coordinates x and y are identical for these two trajectories, and the z-coordinate of the second trajectory is always more or equal to the $z-$coordinate of the original trajectory. Therefore, if a vehicle at some time t is seen from some UAV i on the original trajectory, it is also seen from the same UAV on the second trajectory. This completes the proof of Proposition II.1. □

Proposition II.1 shows that optimal or close to optimal solutions of the optimization problem (6) can be found in the class of high trajectories. That might result in solutions in which vehicles are seen from the UAVs but the distances between the UAVs and the vehicles tend to be unnecessarily large. Therefore, we propose another problem statement in which the distances between the UAVs and the vehicles are taken into account.

Let $c > 0$ be a given constant. We introduce the functions $L_{ij}^c(t, v(\cdot), \omega(\cdot), u(\cdot))$, $j = 1, \ldots, M$, $i = 1, \ldots, K$ as follows: $L_{ij}^c(t, v(\cdot), \omega(\cdot), u(\cdot)) := \frac{1}{d_{ij}(t)}$ if vehicle j is seen from UAV i at time t (here $d_{ij}(t)$ is the distance between vehicle j and UAV i at time t); $L_{ij}^c(t, v(\cdot), \omega(\cdot), u(\cdot)) := -c$ if vehicle j is not seen from UAV i at time t. $L_{ij}^c(t, v(\cdot), \omega(\cdot), u(\cdot))$ can be regarded as a measure of the quality of surveillance (QoS) for vehicle j provided by UAV i at time t. Moreover, we introduce $L_j^c(t, v(\cdot), \omega(\cdot), u(\cdot)) := \max_{i=1,\ldots,L} L_{ij}^c(t, v(\cdot), \omega(\cdot), u(\cdot))$, and it represents the best QoS achieved by the closest UAV for vehicle j at time t. Let $\beta > 0$ and $\gamma > 0$ be given constants. Now, we introduce the following optimal control problem:

$$
\begin{aligned}
&\mathcal{L}^c(v(\cdot), \omega(\cdot), u(\cdot)) := \\
&\quad \min_{j=1,\ldots,L} \int_{t_0}^{t_0+T} L_j^c(t, v(\cdot), \omega(\cdot), u(\cdot))dt \\
&\quad + \beta \sum_{j=1}^{L} \sum_{i=1}^{K} \int_{t_0}^{t_0+T} L_{ij}^c(t, v(\cdot), \omega(\cdot), u(\cdot))dt \\
&\quad - \gamma \int_{t_0}^{t_0+T} (|v(\cdot)| + |\omega(\cdot)| + |u(\cdot)|)dt, \\
&\mathcal{L}^c(v(\cdot), \omega(\cdot), u(\cdot)) \to \sup,
\end{aligned}
\tag{7}
$$

where the supremum is taken over all possible control inputs $v(\cdot), \omega(\cdot), u(\cdot)$. The third term of (7) describes the propulsion energy of the UAVs and can be viewed as "the utilization rate of UAV resources" in terms of energy spent on surveillance. It is obvious that with $\gamma = 0$ the optimization problem (7) becomes close to (6) as c tends to infinity. More precisely, $\mathcal{L}(v^*(\cdot), \omega^*(\cdot), u^*(\cdot)) > \mathcal{L}(v(\cdot), \omega(\cdot), u(\cdot))$ for some control inputs $v(\cdot), \omega(\cdot), u(\cdot)$ and $v^*(\cdot), \omega^*(\cdot), u^*(\cdot)$, implies $\mathcal{L}^c(v^*(\cdot), \omega^*(\cdot), u^*(\cdot)) > \mathcal{L}^c(v(\cdot), \omega(\cdot), u(\cdot))$ if c is large enough.

Problem Statement: Construct a path planning algorithm for the system (1) of K UAVs that maximises the objective function (7) s.t. the constraints (2), (3) and (4).

III. Path Planning Algorithm

Take some whole number $N > 0$, and split the time interval $[t_0, t_0 + T]$ into N subintervals of length $h := \frac{T}{N}$. Now consider the set of functions $v_i(t)$, $\omega_i(t)$, $u_i(t)$ that change their values only at times $t_0, t_0+h, \ldots, t_0+(N-1)h$ and keep their values constant over subintervals $[t_0+jh, t_0+(j+1)h]$, $0 \leq j \leq N-1$. Take some parameters $l_\omega > 0, l_v > 0$ and $l_u > 0$. These parameters specify the levels of quantization of the inputs of (1). Introduce the following collection of inputs:

$$
\begin{aligned}
\omega_i &= \frac{j_\omega \Delta_2}{l_\omega} \quad \forall j_\omega = -l_\omega, -l_\omega+1, \ldots, l_\omega \\
v_i &= \frac{j_v \Delta_1}{l_v} \quad \forall j_v = 0, 1, \ldots, l_v \\
u_i &= \frac{j_u \Delta_3}{l_u} \quad \forall j_u = -l_u, -l_u+1, \ldots, l_u,
\end{aligned}
\tag{8}
$$

where $i = 1, \ldots, K$.

Introduce the following optimization procedure.

OS: Take inputs of (1) for $i = 1, \ldots, K$ belonging the set (8) and changing their values at $t_k, t_k+h, \ldots, t_k+(N-1)h$. Calculate a corresponding trajectory of (1). Choose the inputs (with N collections of inputs applied at $t_k, t_k+h, \ldots, t_k+(N-1)h$) at which maximum for (7) s.t. (2), (3) and (4) over all control inputs from the set (8) is achieved.

It is obvious that for any $t_k + jh$ and any UAV i there exist $(2l_\omega+1)(l_v+1)(2l_u+1)$ possibilities of different inputs from the set (8). Therefore, as we have N time subintervals and K UAVs, we have $[(2l_\omega+1)(l_v+1)(2l_u+1)]^{NK}$ possible sets of inputs. This set of possible inputs can be viewed as some tree of options. When some of the constraints (2), (3) and (4) does not hold, some branch of the tree is stopped, as it is shown in Fig. 3. Specifically, when the constraint (2) is violated, the corresponding branch is removed from the tree. When the constraint (3) is violated at some two branches, we can remove either branch. When the constraint (4) does not hold, we remove the corresponding branch from the three as well. Hence, due to the constraints, the optimization algorithm usually deals with a much smaller number of input sets than $[(2l_\omega+1)(l_v+1)(2l_u+1)]^{NK}$.

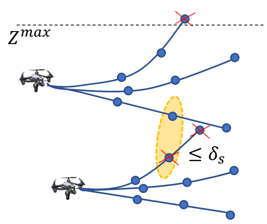


Fig. 3: Illustration of branch cancellation due to the violation of constraints (2), (3) and (4).

It should be pointed out that as the accuracy of the control input parameters increases, the quality of the results provided by the proposed algorithm will also increase, but the time complexity of the algorithm will also increase and may become unacceptable for providing real-time results for the UAVs. In the following section, we conduct simulations with several values of parameters to find a suitable trade-off between the performance of the algorithm and its time complexity and discuss this issue in detail.

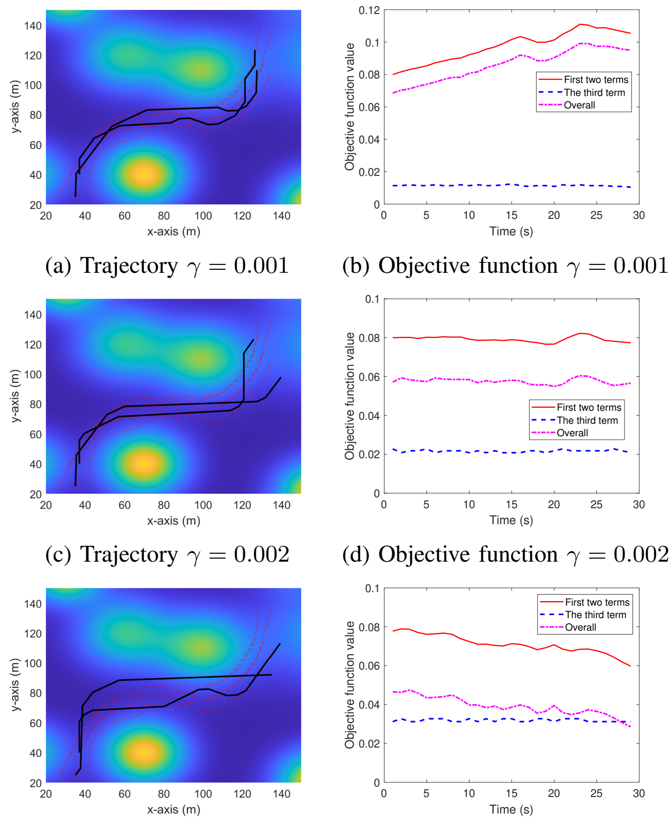
Proposition III.1. *When the parameters N, l_ω, l_v, l_u tend to $+\infty$, the inputs constructed by* **OS** *tend to the global supremum of the optimization problem (7) for the UAVs (1) s.t. (2), (3), (4).*

Proof. Indeed, we can take control inputs $v^0(\cdot), \omega^0(\cdot), u^0(\cdot)$ of the system (1) that is close enough to the global supremum in (7). We can approximate these control inputs with any small precision by piecewise constant inputs. This implies that we can design a sequence of the collection (8) that tends to v^0, ω^0, u^0 when N, l_ω, l_v, l_u increase to $+\infty$. This implies that the value of (7) for the sequence built in **OS** tends to supremum when the quantization parameters of the algorithm tend to infinity. This completes the proof. □

It should be emphasized that this framework results in an asymptotically globally optimal solution. This means that when the numbers of quantization levels of the method increase to $+\infty$, constructed UAV paths tend to be the paths that deliver the global maximum.

The following MPC type procedure [23] will now be applied.

MPC1: Let $t_k := kh$ for $k = 0, 1, \ldots$. We obtain the solution of the optimization problem (7) s.t. (2), (3), (4) on the interval $[t_k, t_k + T]$ by the algorithm **OS**.



(a) Trajectory $\gamma = 0.001$ (b) Objective function $\gamma = 0.001$

(c) Trajectory $\gamma = 0.002$ (d) Objective function $\gamma = 0.002$

(e) Trajectory $\gamma = 0.003$ (f) Objective function $\gamma = 0.003$

Fig. 4: Simulation results in Case 1.

MPC2: Inject the first input of the input sequence obtained in **MPC1**.

MPC3: Return to **MPC1**, **MPC2** at instant $(k+1)$.

IV. Computer Simulations

We demonstrate the effectiveness of the developed algorithm through simulations. We create some mountain-like environments in which groups of ground vehicles move.

We first consider the weight of γ which reflects the UAV resource utilization rate. In a simulated environment (Case 1) shown in Fig. 4, there are two UAVs and five vehicles, and $\Delta_1 = 5$ m/s. The simulation time is 30 seconds for these cases, and other parameters are $\Delta_2 = 0.5$ rad/s, $\Delta_3 = 0.5$ m/s, $l_v = 1$, $l_w = 1$, $l_u = 1$, $d_{safe} = 10$ m, $\alpha = \frac{\pi}{2}$, $Z^{max} = 30$ m, $Z^{min} = 10$ m, $\beta = 0.1$, $h = 1$ and $N = 3$. We present the results of both the UAVs' trajectories and the objective function values under several values of γ. We can see in Fig. 4 that when γ increases, i.e., more attention is paid to the spent energy, the UAVs' trajectories become flatter. The corresponding cost is the reduction of the first two terms of (7), which reflects the surveillance quality. In other words, results for different values of γ in Fig. 4 show a trade-off between the surveillance quality and the UAV resource utilization rate.

We are also interested in the computational time of our algorithm for various values of l_u, l_v, l_ω and N using a personal computer with an Intel Core i7-7500U CPU, and the results are summarized in TABLE I. With the increase of N

TABLE I: Computational time of our algorithm with various values of l_u, l_v, l_ω and N.

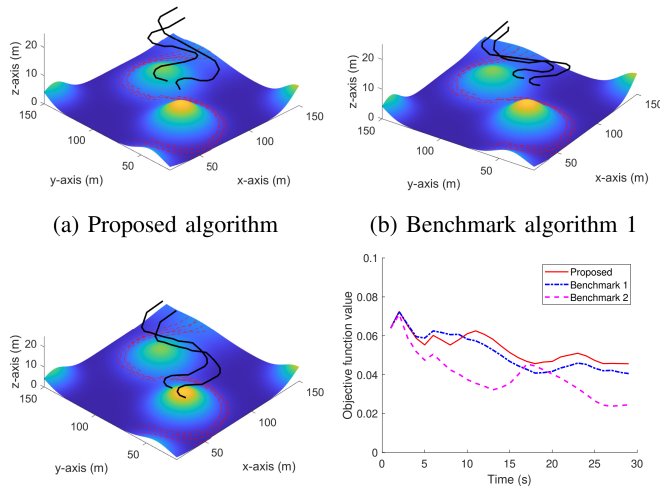
Line	l_u	l_v	l_ω	N	Average time per step (second)
1	1	1	1	3	0.0072
2	1	1	1	4	0.44
3	1	1	1	5	3.08
4	2	1	1	3	0.15
5	3	1	1	3	1.07
6	1	1	2	3	0.14
7	1	1	3	3	1.12
8	1	2	1	3	0.036
9	1	3	1	3	0.45

(see Lines 1-3), the computing time increases a bit less than the theoretical exponential relationship in Section III thanks to the cancellation of invalid UAVs' trajectories. With the increase of l_u (see Lines 1, 4 and 5), the computing time also increases. But, the increasing rate is much smaller than that due to N. This is because the effect of l_u is the base, while N is the exponent, which is consistent with the analyzed complexity in Section III. The impact of l_ω is very similar to l_u. As for l_v (see Lines 1, 8 and 9), it follows the same trend as l_u and l_ω, but the scale is smaller, which is also consistent with the result in Section III. Indeed, the complexity of the presented algorithm will become too large under large values of l_u, l_v, l_ω and N. Small values of l_u, l_v, l_ω are also reasonable, especially for inexpensive UAVs that do not have strong manoeuvrability. For N, we should select it based on usage such as how frequently the ground vehicles may adjust their movement. Moreover, the presented algorithm is intended to run onboard. So, the computing capability of the onboard computer also impacts the selection of N.

To better illustrate the performance, we consider two benchmark methods. One is based on Voronoi partitioning [11], [13], and the other is the standoff tracking method, i.e., the UAV team stays away from the targets by a certain distance. The basic idea of the first method is to first partition the targets into some groups according to their positions and the positions of UAVs and then drive the UAVs towards the centres of the groups. For the second method, the UAVs keep a certain formation and track the centroid of the targets. The proposed method and benchmark methods are applied to Case 2 and Case 3, and the initial conditions of the three methods in each case are identical. γ takes 0.001, and all parameters are the same as Case 1. The multi-UAV trajectories for these three methods are shown in Fig. 5 and Fig. 6.

From Figs. 5d and 6d, we can see that the proposed method outperforms the benchmark methods, and the outperformance is more obvious for three UAVs, see Fig. 6d. The main reason is explained as follows. The proposed method aims at maximizing the worst-case QoS during the flight, reflected by (7). However, the trajectories constructed by the benchmark methods mainly track the centres of the groups of vehicles. These trajectories can give a good performance of QoS in an average manner. But, when we look at each vehicle individually, the worst case by the benchmark methods is worse than that of the proposed method in general.

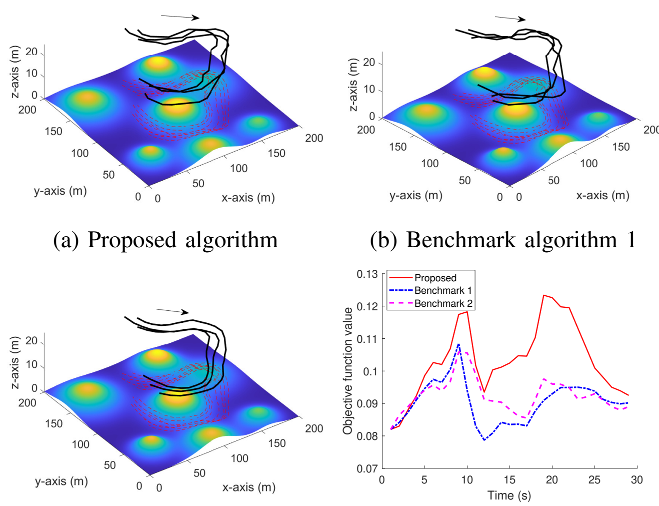
Notice that for comparisons we use the objective function (7) and do not use some more general evaluation criteria, as the main feature of this paper is that we consider the case of very uneven terrain and the goal is to maximize the overall time during which the ground vehicles are observed by the UAVs, i.e. there exists the unblocked LoS between the UAVs and the targets. To the best of our knowledge, there are no other papers on UAV surveillance of ground targets that fully address this issue. Therefore, other known measures of surveillance quality do not fully capture the main issue addressed in this paper.



(a) Proposed algorithm (b) Benchmark algorithm 1

(c) Benchmark algorithm 2 (d) Objective function values

Fig. 5: Simulation results in Case 2. (a) Paths of the UAVs with the proposed algorithm. (b) Paths of the UAVs with the first benchmark algorithm. (c) Paths of the UAVs with the second benchmark algorithm. (d) Objective function values.



(a) Proposed algorithm (b) Benchmark algorithm 1

(c) Benchmark algorithm 2 (d) Objective function values

Fig. 6: Simulation results in Case 3. (a) Paths of the UAVs with the proposed algorithm. (b) Paths of the UAVs with the first benchmark algorithm. (c) Paths of the UAVs with the second benchmark algorithm. (d) Objective function values.

V. Conclusion

In this correspondence, the problem of navigating a team of UAVs for surveillance of ground vehicles on uneven terrain was investigated. In the studied problem, UAVs with mounted video cameras are to be navigated with the aim to monitor as close as possible several ground vehicles moving on uneven terrain. An effective and optimal in some sense collision-free navigation algorithm was proposed. Propositions II.1 and III.1 provided some theoretical justification of the multi-UAV path planning algorithm as these rigorously proved statements show that the solution delivered by this algorithm converges to the optimal solution as some parameters tend to infinity. The obtained navigation algorithm is also capable to design safe collision-free UAV trajectories.

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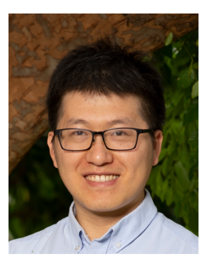

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