Monitoring Road Traffic with a UAV-based System

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Abstract—**Unmanned Aerial Vehicles (UAVs) are becoming an attractive solution for road traffic monitoring because of their mobility, low cost, and broad view range. Up to now, existing traffic monitoring systems based on UAVs only use one UAV with fixed trajectory to extract information about vehicles. In this paper, we propose a road traffic monitoring system using multiple UAVs. We develop a method to generate adaptive UAVs trajectories, which is based on the tracking of moving points in the UAV field of view. Also we generate UAVs trajectories using mobility models that are usually used to model vehicles mobility. UAVs monitor the traffic on a city road, they are responsible for collecting and sending, in real time, vehicle information to a traffic processing center for traffic regulation purposes. We show that the performance of our system is better than the performance of the fixed UAV trajectory traffic monitoring system in terms of coverage rates and events detection rates.**

Keywords—Unmanned Areal Vehicles (UAVs), road traffic monitoring, UAVs trajectories, events detection, estimation of events duration.

I. Introduction

Unmanned Aerial Vehicles (UAVs), also known as drones, are used in an increasing number of civil and commercial applications. Among these applications, Road Traffic Monitoring (RTM) systems constitute a domain where the use of UAVs is receiving significant interest. This paper addresses the design of a UAV-based system for the management of road traffic within a city.

Several RTM systems already exist. Their activity is usually structured around two main tasks. The first one concerns the detection of events like car accidents and speeding. The second one focuses on traffic regulation purposes to avoid traffic congestion or traffic jams.

To implement these two tasks, RTM systems should first collect traffic data from deployed devices. Traffic data can consist of the number of vehicles in a specific area, the number of vehicles passing through a given point. Sophisticated data collection devices can further estimate the position, the speed of a vehicle. The data should then be transmitted to control centers to be processed. The collected data can automatically trigger emergency measures in case of a serious event (car accident, bank attack) [1][2][3], or it can be appended to previously collected data to compute traffic statistics [2][4]. Actions are then undertaken to manage the events or to regulate road traffic (read lights, traffic displays).

Several current systems collect traffic data through sensors and cameras [5]. These systems allow for the monitoring of a specific area. Other solutions use embedded sensors like mobile phones or GPS devices to locate vehicles. More information such as status of traffic and alternative routes are collected but at the cost of a strong system constraint since every vehicle must be equipped with a localization device.

We now address the advantages and drawbacks of using UAVs in the context of an RTM system. The first advantage of UAV based RTM systems is that they allow the monitoring of a larger area. UAVs can move from one area to another [6]. The field of view is not limited to a given area just like with RTM systems using sensors and cameras. Moreover, UAVs can perform vehicle identification when equipped with cameras and image processing capabilities, without the need for embedded sensors within cars. UAVs can be deployed in an area of interest at no additional cost for the infrastructure. On the other hand, UAVs are limited by battery life and their use causes privacy issues.

Two main UAV based RTM systems already exist. In the first system, one or multiple UAVs are used to collect data from multiple sensors placed on the roads [3] [7]. The idea is that the UAV continually flies over ground sensors, establishes a connection with them and then exchanges messages to gather information. In [8], the UAV communicates only with the clusters heads nodes. In the second system, only one UAV is responsible for measuring target parameters. The UAV is equipped with image processing capabilities that allow it to observe and measure the relevant parameters about the vehicles [9] [10]. In those two systems the UAV trajectory is predefined.

In this paper, we propose a UAV based RTM system and address the issue of UAV trajectories. The purpose is to show the advantages that could bring the use of multiple UAVs to monitor the traffic within city roads. Since it is not reasonable to address an exhaustive monitoring of all the vehicles in the city area, and due to a limited number of UAVs, we study the impact of mobile UAV trajectories on the event detection rate and the number of controlled vehicles. We generate UAVs trajectories to monitor as many vehicles as possible for as long as possible. In the first proposal, UAVs trajectories are computed according to the movement of the vehicles. First, vehicles are grouped into clusters, and then the UAV trajectories are computed following the centers of gravity of these clusters. In the second proposal, UAVs trajectories are generated according to a mobility model.

The rest of the paper is organized as follows. In Section II, we present the context. In Section III, we analyze simulation results. We conclude in Section IV.

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II. A NEW ROAD TRAFFIC MONITORING TECHNIQUE

The goal here is to monitor vehicles moving on city roads. These vehicles are considered as targets that need to be tracked. To design a realistic UAV based system we need to select a method to collect information about vehicles, we also need to organize the deployment of UAVs over the coverage area, and finally we must generate optimal UAVs trajectories to cover as many targets as possible.

A. Collecting information about vehicles

Several parameters can be observed and measured according to the devices that are deployed over the coverage area: vehicle position, speed, and direction, the number of vehicles within an area, the number of vehicles passing through a given point (a gate, an intersection, a crossing). Specific events can be detected through value changes of the above mentioned parameters. For instance, speeding can be detected when the speed of a vehicle exceeds a given limit. On the other hand, traffic jams can be detected when the speed of several vehicles falls below a given threshold.

In this paper, we consider multiple UAVs that are equipped with image processing capabilities that allow them to observe and measure the relevant parameters with perfect estimation. We assume that the detection of targets in the FoV is always possible, i.e., no obstacle is obstructing the UAV line of sight. Also, we assume that UAVs can temporarily change their altitude to prevent collisions, and that UAVs exchange information about vehicles they are tracking (identifier, position).

B. Deploying UAVs over coverage areas

The major issue here is to evaluate the number of UAVs that are needed to cover a city area, even if we consider a static UAV allocation. Because it is not possible to deploy an unlimited number of UAVs, a single UAV must be assigned to a set of targets. A possible solution to reduce the number of UAVs is to form target clusters and to assign a UAV to each cluster. To constitute group of targets, we will use almost the same technique as in sensor network or VANETs (Vehicular Ad-Hoc Networks). To do so, the following parameters can be used: distances between targets, target velocities, and directions of movement. The distance criterion is a natural criterion to constitute groups of targets. We are also interested in constituting stable groups, i.e., groups whose constitution will not significantly change from one assignment update to another. In this context, the smaller the difference between the group members velocity, the more stable the group will be. The cluster will also be more stable if the members have the same moving direction.

We propose an algorithm (Algorithm 1) to perform this clustering step. We think about this step as an off-line step that allows system operators to estimate the number of UAVs. We first assume that the total number of targets is known, and that all the targets are perfectly identified with the following parameters: label, position, speed, direction of movement. These parameters could have been measured by other means and stored in a database. The algorithm inputs are presented in TABLE I. In this paper, three criteria are selected to perform the clustering: the distance between the central target and a potential member of the group, the speed difference these two targets, and their direction of movement. The first criterion is mandatory to perform the clustering. The other two criteria are optional, i.e., they can be used in conjunction with the first criterion. We first choose a target that will be the central target of the first group of targets. This target is randomly chosen. All the N targets are numbered from 1 to N and a number is drawn according to uniform distribution. Then we review all the targets and we assign a target to the current group when the target satisfy one or several conditions according to the above mentioned criteria:

- the distance between the central target and the potential member of the group is lower than a given threshold, equal to the radius of the UAV's FoV, denoted r;
- the speed difference between the two targets is below a given threshold, denoted V_d;
- the direction of movement of the central target is the same as the one of the potential member.

At this point, we must remove all the selected targets so they will not be considered in future steps. We go on choosing another central target till all the targets are placed in a set of targets.

TABLE I: Algorithm inputs

T_{nb}	Targets numbers	G	Groups members
D	Max distance value	V	Max speeds difference
P_t	Target position	M_t	Target direction
V_t	Target velocity	$compt$	Covered targets
T_{tag}	Target tag	T_{id}	Target id
C_{id}	Central target id	P_c	Central target position
M_c	Central target direction	C_{tag}	Central target tag
V_c	Central target speed		

Algorithm 1: Uniform method

$j = 1$; $compt = 0$;
while $compt < T_{nb}$ **do**
  while $C_{tag}(j) == 1$ **do**
    $P_c(j)$ = Uniform (P_t) ;
  $C_{tag}(j) = 1$; $G(j, j) = C_{id}(j)$;
  $compt = compt + 1$;
  for $i = 1$ *to* T_{nb} **do**
    if $(T_{tag}(i) == 0)$ & $(i \neq j)$
    & $(M_t(i) == M_c(j))$
    & $|V_t(i) - V_c(j)| < V$
    & $|P_t(i) - P_c(j)| < D$ **then**
      $G(j, i) = T_{id}(i)$;
      $compt = compt + 1$;
      $T_{tag}(i) = 1$
  $j = j + 1$

C. Designing UAVs trajectories

Now that we have an estimate of the number of UAVs, we address the design of UAV trajectories. Three approaches were studied and presented in Fig. 1.

For the existing method, the UAV trajectory is fixed, and guided by predefined Points Of Interest (POI) [2] [11]. POIs are points where there is high traffic (intersection for example). A single UAV is used.

Our first proposal is based also on the concept of POIs and the use of multiple cooperative UAVs. The multiple UAVs are capable of of identifying the targets in their FoV and estimating their positions and speeds, and exchange those information between each other and with a central point. UAVs trajectories are adaptive and POIs are mobile. This method is referred to as the mobile POI method. In this method, the objective is that every UAV keeps in its FoV the maximum number of targets, and keeps tracking them as long as possible. Because the trajectories of the UAV will depend on the motion of the targets in their FoV, the mobiles POIs that will be followed are the centers of gravity of targets groups. The center of gravity P_g of a target group with members number nb, and with positions P_{gt} is computed as follow:

$$P_g = \frac{\sum_{k=1}^{nb} P_{gt}(k)}{nb}$$

UAVs trajectories are calculated according to the motion of the centers of gravity of their groups of targets, so that UAVs always fly over those computed positions. The motion of the center of gravity depends on the motion of targets within the group, but the motion also depends on incoming and outgoing targets within the FoV of the UAV. In this case, UAVs speed is variable to adapt to the trajectories of the centers of gravity. The constitution of the group may change over the time, and the velocity of the members is the principal cause.

The second proposed approach relies on vehicular mobility models, we call it Vehicular mobility based method. The UAV trajectory is generated according to these models. In this method we use also multiple UAVs to do the monitoring task. We use the same mobility model as the one we used to simulate target movements. The trajectories of UAVs are guided by points randomly generated by the Shortest Path Map-Based Movement model. So UAVs will move exactly above roads, and do observation regarding the targets in their FoV. So with this technique, the chance to observe targets and events is higher. The speed interval is an essential attribute to define, in fact the speed of UAVs must be close to the speed of the targets to observe as long as possible targets. UAVs speeds are uniformly distributed random variables.

III. Simulation results

In this section, we present the simulation tool, simulation parameters, and simulation results.

A. Simulation tool

To compute event rates and event duration, the first alternative is to use real mobility traces of cars moving on city roads, and the second alternative is to use a simulator to generate car mobility traces based on real cities maps. For the real traces we worked on dataset of mobility traces of taxi cabs in Rome, Italy, and dataset of mobility traces of taxi cabs in San Francisco, USA, provided by CRAWDAD [12], to evaluate the performance of our contribution. Our methods are based on the clustering of targets and assignment of an UAV to a group of target, but with those real traces it is not possible to show the pertinence of our contribution, because taxi cabs are very far from each other. So we decide to use instead a simulator and generate mobility traces of a higher number of vehicles.

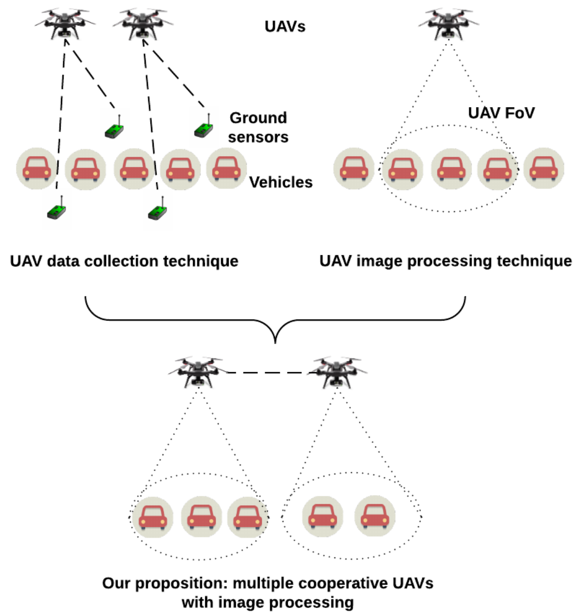

Fig. 1: Traffic monitoring techniques

We opted for the Opportunistic Network Environment (ONE) simulator [13]. ONE is an opportunistic networking evaluation tool that can integrate real-world maps. We use the Shortest Path Map-Based Movement model (SPMBM) to compute the path between two points on a map: a departure point and an arrival point. Paths are computed according to the Dijkstra's shortest path algorithm. First, we fix the number of cars on the map. We recall that the cars are the targets that need to be tracked. Target positions are drawn according to a uniform distribution, i.e., the abscissa x and the ordinate y of a target are uniformly distributed random variables. The speed of a target follows also a uniform distribution and the speed remains constant over the simulation duration. Once the target arrived to its designated arrival point, it waits for a random amount of time before it moves on the another arrival point.

UAVs will be flying over the area, trying to collect as much data as possible. We will evaluate the coverage rate of the cars, the percentage of occurrence of the abnormal events (congestion, and infractions), and the duration of detected events.

B. Simulation parameters

We work on the Helsinki downtown area ($4500m \times 3400m$) and we consider scenarios with 1000 targets spread out over the area. Vehicle speeds are uniformly distributed in two different intervals according to the simulation run. The interval is $[10m/s, 15m/s]$ when we estimate the requested UAVs number, and the interval is $[0, 15m/s]$ when we estimate tracking parameters. The wait time when the targets arrived to its destination is null. Other parameters are in Table II.

TABLE II: Simulation parameters

Parameters	Value	Parameters	Value
Simulation time	1000 s	Sampling interval	1 s
Maximal velocity of cars	15 m/s	Minimal velocity of cars	10 m/s
Difference of velocity (V_d)	1 m/s	Cars numbers	1000
UAVs altitude (A)	200 m	Radius of the UAV's FoV (r)	100 m

C. Number of requested UAVs

We implemented the clustering method presented in the previous section. Three approaches are compared. The first one relies on the distance criterion, the second one relies on two criteria: the distance and the velocity. The third one also relies on two criteria: the distance and the direction of movement. Simulation results are presented Fig. 2.

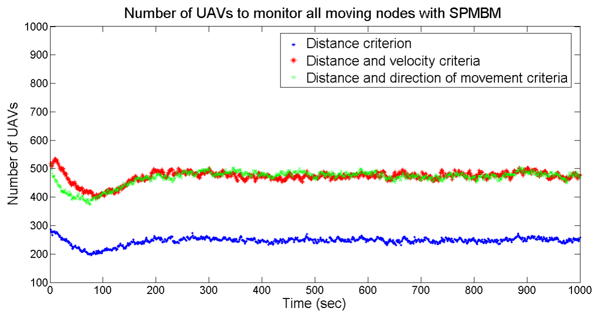

Fig. 2: Number of UAVs

We observe that the number of requested UAVs converges toward a stable value after a transient period of approximately $200s$. The value is around 250 to cover the 1000 targets when the clustering is performed using the distance criterion. This number increases to 450 when the distance criterion is used in conjunction with another criterion (velocity or direction of movement). The two last approaches give higher values because they are more restrictive to build the clusters. The results provide an order of magnitude for the number of requested UAVs.

With the first approach, around 250 UAVs is needed to cover 1000 targets. The number of requested UAVs is too high to allow for a realistic implementation of the RTM system, and too high for the simulator. So we decide to reduce the number of UAVs to use, so for sure as consequence the coverage rate will decrease. We expect that 25 UAVs could cover 100 targets, i.e., achieve a coverage rate of 10%. So we will do simulation for a number of UAVs between 5 and 50 to check if the ratio between the targets number and the UAVs number is linear. We will as well compare the performance of existing monitoring methods and proposed ones.

D. UAVs tracking methods

The number of cars is 1000 and they are moving according to the Shortest Path Map-Based Movement. The velocity of cars is between 0 and $15m/s$, with no wait time. We did simulation for different number of UAVs.

The proposed tracking methods are evaluated according to the following parameters: the coverage rate, the detection rate of speeding violations, the detection rate of speeding vehicles, the average duration of the detected speeding violations, the detection rate of congestion events, and the average duration of the detected congestion events. That is how we evaluate the parameters:

- Coverage rate: percentage of vehicles in the UAV's FoV.
- Detection rate of speeding violations: speeding violations are detected when vehicles velocities exceed $12m/s$.
- Detection rate of speeding vehicles: speeding vehicles are detected when their velocities exceed $12m/s$.
- Average duration of the detected speeding violations.
- Detection rate of congestion events: congestion events are detected when vehicles velocities are lower than $3m/s$.
- Average duration of the detected congestion events.

The UAV trajectories are computed according to the three approaches presented in the previous section. In the case of the mobile POI method, and for the vehicular mobility-based method, the speed of the UAVs is variable. The speeds are uniformly distributed in the interval $[0, 15m/s]$, and the initial locations of the UAVs are uniformly distributed over the coverage area.

- In the mobile POI method, the trajectory of a UAV is defined by the center of gravity of its corresponding group of targets.
- In the method based on a vehicular mobility model for the UAVs, UAVs trajectories are generated according to this mobility model.
- In the exiting method (Fixed POI method and Stationary Fixed POI method), at the beginning of the simulation, all UAVs are located at the same fixed starting point. Then they move to their respective POIs. In the case of the Fixed POI method, UAVs fly over the POIs according to a random waypoint model over a delimited circular area whose center is the POI and whose radius is $200m$ with a fixed velocity ($12m/s$). In the case of the Stationary Fixed POI method, UAVs are hovering over the POI (with a null speed).

In this existing method only one UAV is used to monitor all the fixed POI. But, in the Simulation, to be fair, the number of UAVs will be equal to the number of POIs. We assume that UAVs exchange information so collisions between UAVs are avoided. We also assume that the collected information is sent to a processing center using 4G connections.

The results of coverage rates, events detection rates, and events duration of the three type of trajectories for different number of UAVs are listed in Table III.

For the Fixed POI method with a random movement of UAVs around the POIs, The detection rate of speeding vehicles can go from 32%, with 5 POIs, to 80.87%, with 50 POIs.In fact, when the number of POIs gets higher, an additional number of cars will be observed. So the coverage rate will be higher, and the detection rate of events will be higher.

The real average duration of the congestion events is $575.66sec$ and the real average duration of speeding violations is $179.41sec$. The average duration of detected congestion events, goes from $94.16sec$ in the case of 5 POI, down to $74.29sec$ in the case of 50 POI. In deed, when the number of POI increases the time spent by an UAV over a given area decreases, so the observed duration of events will decrease and will not be close to reality.

Like the Fixed POI method, in the Stationary Fixed POI method, when the number of POIs gets higher, the coverage rate will be higher as well as detection rate of events. For 50 POIs, when UAVs are stationary, the coverage rate is 16.31% while it is equal to 19.27% when the UAVs are moving randomly around the 50 POIs. In fact, when UAVs are flying exactly over the POIs (like fixed cameras), only cars in the FoV of UAVs will be observed. This explains the lower rates of coverage and detection events comparing to the fixed POI method with a random movement of the UAVs. This is confirmed for all the scenarios.

For example, for 50 UAVs, the average duration of the detected congestion events, is equal to $109.02sec$ in the case of Stationary Fixed POI method, and equal to $74.29sec$ in the case of Fixed POI method. Actually, when UAVs are stationary, slow vehicles will remain longer in the FoV of the UAVs, so the average duration of the congestion events will be better than for the case when the UAVs are randomly moving around the POI. And fast vehicles will go out faster from the UAVs FoV, so the average duration of the speeding violation will be lower.

Our proposed methods exhibit better performance in terms of coverage rate, event detection rates and event average duration. The coverage rate is better (up to 28.62% in the case of Mobile POI method with 50 UAVs). The detection rate of speeding violation is better (up to 30.09% in the case of Vehicular mobility based method with 50 UAVs). Also the values of the events duration are the closest to the reality. In deed, the proposed methods are based on mobile UAVs trajectories, so a higher number of cars will be observed in the trajectory of the UAVs. They are more suited to observe the evolution of events in time since they are not based on fixed points. Also, when the number of UAVs increases, the performances are better because an additional number of targets will be observed.

Also the average duration of the detected speeding violation is better in the mobile methods than in the fixed methods because in the mobile method the UAVs are more likely to observe fast moving vehicle in their mobile trajectory.

The value of the average duration of the detected congestion events in the Mobile POI methods is higher than in the vehicular mobility based method ($206.92sec$ for 50 UAVs). This is due to the fact that in the Mobile POI method, the UAVs are adapting their trajectory according to the center of gravity of their groups of targets so they are more likely to keep in their FoV a group of target much longer especially those with more slow motion.

Proposed methods always perform better than the Fixed methods. The reason is when trajectories are mobile and not attached to fixed points more targets will be covered. Also, we observe that for a small number of UAVs performance are almost the same for all methods, but from 25 UAVs we observe a notable amelioration in our methods.

The estimation that we did early was that 25 UAVs would cover 10% of targets, but with our proposed methods the coverage rate is around 17%. This confirms the pertinence of our contribution.

IV. Conclusion

In this paper, we proposed methods to monitor the road traffic using multiple cooperative UAVs. These methods have two goals. The first one is to cover the largest number of targets and the second one is to detect the highest number of events to be monitored. The proposed methods are based on mobile UAVs trajectories. In a first approach, the trajectories are adapted by moving points which are the centers of gravity of target groups in the UAVs's FoV. In a second approach, trajectories are generated by a mobility model.

To evaluate the performance of our methods, we compute the coverage rate, the detection rate of speeding violations, speeding vehicles, and congestion events, the average duration of the detected congestion events, and detected speeding violations for a different number of UAVs. We observe better performance regarding coverage and event detection comparing to methods based on fixed trajectories.

In this paper, the detection of congestion events is based on the detection of a single vehicle with a low speed. We can improve the detection process by better characterizing a traffic jam. Moreover, sharing information among UAVs could also improve the detection rates. This is left for future work.

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TABLE III: The results of the existing tracking methods

(5 POI, 5 UAVs) / 1000 targets	Stationary Fixed POI method	Fixed POI method	Mobile POI method	Vehicular mobility based method
Coverage rate	3.01%	3.46%	4.32%	3.4%
Detection rate of speeding violations	2.88%	3.39%	3.98%	3.6%
Detection rate of speeding vehicles	30.31%	32%	45.11%	43.03%
Average duration of the detected speeding violations	17.18 sec	19.75 sec	18.14 sec	17.59 sec
Detection rate of congestion events	2.88%	3.11%	4.50%	3.39%
Average duration of the detected congestion events	118.62 sec	94.16 sec	88.62 sec	64.39 sec
(10 POI, 10 UAVs) / 1000 targets				
Coverage rate	5.66%	6.11%	7,42%	7.07%
Detection rate of speeding violations	6.13%	5.91%	6,54%	7.38%
Detection rate of speeding vehicles	44.95%	46.84%	63,40 %	66.73%
Average duration of the detected speeding violations	16.71 sec	18.65 sec	20,75 sec	23.34 sec
Detection rate of congestion events	5.42%	5.36%	8,61%	5.91%
Average duration of the detected congestion events	115.55 sec	86.14 sec	111,56 sec	66.13 sec
(20 POI, 20 UAVs) / 1000 targets				
Coverage rate	9.65%	10.63%	13.78%	12.45 %
Detection rate of speeding violations	8.99%	10.12%	12.95%	12.95%
Detection rate of speeding vehicles	58.83%	60.49%	82.12 %	82.53%
Average duration of the detected speeding violations	16.48 sec	17.43 sec	32.49 sec	33.51 sec
Detection rate of congestion events	9.52%	10.11%	14.83%	11.63%
Average duration of the detected congestion events	112.91 sec	79.27 sec	139.9 sec	100.54 sec
(25 POI, 25 UAVs) / 1000 targets				
Coverage rate	11.46%	12.82%	17.39%	17.15 %
Detection rate of speeding violations	10.41%	11.72%	16.44%	18.18%
Detection rate of speeding vehicles	60.29%	62.16%	90.02 %	89.39%
Average duration of the detected speeding violations	16.24 sec	17.1 sec	37.67 sec	41.36 sec
Detection rate of congestion events	11.8%	12.81%	18.62%	15.42%
Average duration of the detected congestion events	114.96 sec	82.04 sec	152.9 sec	125.18 sec
(30 POI, 30 UAVs) / 1000 targets				
Coverage rate	13.19%	15.34%	19.8%	19.36%
Detection rate of speeding violations	11.8%	13.97%	18.43%	20.75%
Detection rate of speeding vehicles	64.86%	69.02%	90.43%	90.02%
Average duration of the detected speeding violations	15.57 sec	16.59 sec	42.28 sec	47.42 sec
Detection rate of congestion events	13.83%	15.41%	20.17%	17.23%
Average duration of the detected congestion events	114.25 sec	80.99 sec	165.16 sec	138.20 sec
(40 POI, 40 UAVs) / 1000 targets				
Coverage rate	14.98%	17.66%	25.81%	25.88%
Detection rate of speeding violations	13.74%	16.5%	25.34%	26.06%
Detection rate of speeding vehicles	70.89%	76.29%	93.13%	93.13%
Average duration of the detected speeding violations	15.25 sec	16.25 sec	56.02 sec	57.13 sec
Detection rate of congestion events	15.8%	17.92%	24.67%	23.63%
Average duration of the detected congestion events	112.62 sec	78.46 sec	192.30 sec	181.45 sec
(50 POI, 50 UAVs) / 1000 targets				
Coverage rate	16.31%	19,27%	28.62%	28.28%
Detection rate of speeding violations	15.23%	18.27%	28.03%	30.09%
Detection rate of speeding vehicles	75.67%	80.87%	93.95%	93.76%
Average duration of the detected speeding violations	14.65 sec	15.95 sec	62.15 sec	63.72 sec
Detection rate of congestion events	17.24%	19.59%	27.48%	27.15%
Average duration of the detected congestion events	109.02 sec	74.29 sec	206.92 sec	191.54 sec

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