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TECHNICAL PAPER

Aerial cooperative multi-robot system for remote sensing and automated victim search

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Abstract
This paper presents a distributed coverage control scheme for initially rapid scanning of the environment and then automated victim search in a large-scale firefighting scenario using a cooperative multi-agent system. The quick and efficient reaction of the disaster recovery team can significantly decrease damages and losses. Therefore, a comprehensive map of the affected area immediately after disaster occurred, leads to quickly initial assessment of damages, economic losses and casualties, which can highly improve the efficiency of further relief actions. We considered a firefighting scenario in which fixed-wing UAVs initially fly over the affected area and accomplish a generally and quick scan to identify the critical sections where the fire caused more damage and had a high intensity, severity and spread rate. Then, multi-rotors hover as close as possible to exactly locate the victims and survivors or also damaged infrastructure for more detailed information, and then, firefighters can plan the rescue mission more efficiently. We applied a distributed coverage control scheme so that a heterogeneous multi-agent system cooperatively could explore the affected area and search for the exact location of probable victims or survivors. To achieve this goal, UAVs collaboratively build the cognitive maps including target probability map (TPM) and uncertainty map (UM). Then, based on cognitive map and also their prediction of the next moves of themselves and their neighboring agents as well, UAVs make decision about their optimal collision-free paths. The efficiency of the implemented algorithm is demonstrated by comparison between cooperative and non-cooperative methods. The results indicate that in cooperative distributed scheme, coverage percentage and global average uncertainty converge to their admissible maximum and minimum value in a considerably less time, respectively.

Keywords Disaster recovery · Heterogeneous cooperative multi-agent system · Optimal coverage control · Distributed predictive control · Disaster management

1 Introduction

In recent decades, single-UAV systems have been used for military purposes such as border search and surveillance, target detection and attack and also civilian applications including wildfire monitoring and firefighting, traffic monitoring and management, ad hoc networks and disaster monitoring [1]. However, in wide area applications, using a cooperative team of UAVs seems to be more efficient than a single UAV. Multi-UAV system has advantages over a single UAV which include scalability, lower cost, smaller radar cross-section, faster completion of the mission and reliability. Mission area of a single unmanned vehicle is restricted due to its sensors and communication range [2], while cooperation of multiple agents makes it possible to act in much wider area. Each agent can do the mission in a part of the whole area with respect to its sensor and communication range, and then sharing information with other agents, they can collaboratively accomplish the mission over the whole area in a large-scale application. In addition, there is no need to deploy large-scale UAVs capable of long-endurance flight which means that there is no need to fueled UAVs. So, the cost and radar cross-section will considerably decrease [3]. The speed of mission completion also will increase considerably with higher number of agents [4]. Moreover, when one agent fails for any reason, not only will the whole task

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not fail but other agents will also complete the mission by reconfiguration in their distribution.

Due to high maneuverability, large-scale operational range, high security and the possibility of accessing hard-to-reach places, UAVs equipped with a computer vision system are very suitable and practical options for monitoring firefighting operations or even automatically executing firefighting missions [5]. With respect to the significant advances made in electronics, computer science and digital cameras, and on the other hand, considering the capabilities mentioned for UAVs, which enable the monitoring of firefighting operations as well as remote control with minimal risk to life, remote sensing has become one of the most common tools in forest monitoring and wildfire disaster management in recent decades [6].

Currently, common remote sensing systems for wildfire monitoring include ground-based monitoring systems such as wireless sensor network or cameras mounted on fixed bases, helicopters and manned aircrafts, as well as satellite imagery [7]. Ground-based systems are not suitable for large-scale areas due to limitations in monitoring range. Satellite images may not have enough resolution to extract details. Helicopters and manned airplanes are also expensive and increase costs. All these factors along with the high capabilities of UAVs that have already been mentioned, work hand in hand to make remote sensing with the help of UAVs equipped with computer vision the best, most effective, least dangerous, safest and cheapest solution for firefighting.

Despite the capabilities that drones can add to the wildfire control team such as the ability to fly to hard-to-reach places, saving time which is very important to reduce damages and casualties, and also send on-line videos from the scene to the crisis control unit and operational teams, compared to the other mentioned methods, suffer from a short life span especially the inexpensive small drones. To solve this deficiency and fix this defect in this amazing solution to low-risk remote firefighting, the use of collaborative multi-agent system can be very attractive and pioneering. Multi-UAV systems can search the area rapidly due to their cooperation, and as a result, they accomplish the initial scanning in the shortest time. They can tell the disaster control unit or operational teams where the most critical points are, where infrastructures suffer the most damage and where the most casualties are. They can also just fly over the area and monitor the surveillance region or gather information and forecast live streaming to the disaster control unit. It may also be necessary to transport or deliver cargo such as food or medicine from point to point. Moreover, UAVs can build a comprehensive map of the area cooperatively which includes important information for relief actions such as the location of victims or survivors and damaged infrastructures. They can track the fire front and predict the fire behavior which can help the operational teams to prevent the fire from spreading further.

For intelligence and autonomous firefighting, the drone must be equipped with sensors so that it can record images and extract information by image processing techniquecs. Digital cameras, infrared cameras or a combination of the two are among the options that are used to analyze the color, motion and geometry of fire. Infrared cameras can be used in situations where the light is low, or there is a lot of smoke. To increase the accuracy, reliability and robustness of fire detection algorithms and decrease the false rate, the combination of these two cameras can be used as well [6].

However, the use of drones in firefighting especially large-scale fire such as forest fire may also come with limitations. In such situations due to large-scale fire, the land surface temperature may reach up to 1300 °C [8] which means that the surrounding temperature reaches several hundred °C and can extremely damage the battery of the UAVs or reduce the battery life and so the endurance of the UAVs [9]. This issue can be solved by using swarm of UAVs as explained before. Due to UAVs high maneuverability, there is no concern about the hardware equipment such as camera which is necessary for image processing techniques in UAVs' autonomous operations. In [8], a InReC R500 camera is deployed which its temperature range is −4–500 °C. Deploying image processing techniques, the authors detected fire at altitude of more than 15 m among thick smoke. In a large-scale fire area such as forest fire, the surveillance region will be filled with thick and huge smoke. Therefore, using infrared cameras allows the UAVs to see through smoke and monitor the behavior and development of the fire, detect and extract critical sections and also localize or track targets. However, since one of the factors which cause fire spread in large-scale areas such as forests is strong wind, stability of UAVs over fire is a challenging issue.

2 Related works

Forest fire is a natural disaster which usually starts by human negligence or arson and can burn thousands of square kilometers. Firefighting is a very dangerous operation in which the fire front has to be identified to stop the fire through analyzing its behavior and development and then detecting the next probable points. Lack of information about fire front usually leads to the increase in damages and economic losses as well. Moreover, the ability to detect the boundaries of the wildfire is a crucial aspect in a wide area. According to what mentioned in the previous section, using a cooperative multi-UAV system can be an attractive and efficient solution for wildfire fighting. Thus, in [10], the authors presented an autonomous system that works in real time to estimate the propagating boundary. For this purpose, a fleet of low-cost unmanned aerial vehicles that can be deployed quickly were proposed to be used in monitoring a wildfire. The authors in [11] designed a distributed control framework for a collaborative team of multiple UAVs to monitor the wildfire closely and track its development precisely. A changing environment was assumed, and the UAV team was designed in a way that could avoid in-flight collisions and cooperate with each other to achieve the main goal which was maximum coverage over the affected area, tracking the fire front and predicting its development. In [12], the authors proposed deployment of multiple cooperative fixed-wing UAVs for monitoring, behavior analysis and predicting the development of the fire front. A deep learning method was used to control the UAVs motion in order to achieve maximum coverage during forest fires. The authors of [13] proposed a solution for path planning of multiple cooperative fixed-wing UAVs for fire front development monitoring. The terrain, fire propagation process and dynamics of the agents are modeled. A fleet of UAVs equipped with thermal cameras is considered, and agents' flight is assumed at various fixed altitudes. However, in a firefighting mission in regions such as forest or urban environments, there are many obstacles such as trees and tall buildings, and it is necessary for the multi-agent system to be able to avoid these obstacles. In [14], the authors addressed obstacle avoidance for a swarm of UAVs in a search and rescue mission.

In order to successfully accomplish a firefighting mission, the operational team must have a good understanding of the situation in the disaster area and have sufficient information about the environment in order to be able to plan any operation efficiently. Therefore, an auxiliary aerial team consisting of multiple UAVs can provide very useful information during operations by covering the environment and tracking fire front. The authors of [15] have proposed a multi-UAV system for cooperative wildfire coverage and tracking. In [16], authors have also developed a multi-UAV distributed decisional architecture in the framework of the AWARE Project together with a set of tests with real unmanned aerial vehicles (UAVs) and wireless sensor networks (WSNs) to validate this approach in disaster management and civil security applications. There were two groups of UAVs ready to fly. The first one was equipped with an infrared camera, and the second one with the node deployment device was charged with three sensors. Missions performed with real UAVs in the experiments of the AWARE Project were carried out in 2009. Implementation of the mission comprises sensor deployment, fire detection and making fire stop burning and also multi-UAV surveillance. The results of an automated firefighting mission using a heterogeneous team of UAVs are presented in [17] as well. Multiple UAVs with different capabilities were used to collaboratively detect fire on the ground or on the facade of tall buildings and then try to extinguish the fire by throwing a blanket or spraying water.

The aerial aiding system can forecast the gathered information to the disaster control unit for on-line planning and acting based on this information as well. An aerial sensor network presented in [18] consists of small-scale, battery-powered and wirelessly connected UAVs equipped with cameras for disaster management applications. In the proposed multi-agent system, multiple quadcopters fly in the formation to accomplish a predefined mission collaboratively. Cooperative UAVs will fly over a disaster area such as wood fire or a large traffic accident and forecast information to the disaster management team in the form of high-quality sensor data such as images or videos. The work of [19] proposed a multi-agent system composed of multiple quadcopters for wildfire monitoring. The authors considered a cooperation problem between multiple quadcopters as a distributed network that a consensus-based solution was presented for it. In [20], multiple cooperative quadcopters are deployed as a multi-agent system for surveillance and monitoring a wildfire in a large-scale area. Based on physical model of fire front development, a propagation model and also a Kalman filter-based method is presented to estimate the rate of fire development. The problem is solved by a consensus-based method. A multi-agent system comprising multiple cooperative UAVs is presented in [21] for wildfire monitoring in remote and hard-to-reach areas. For this purpose, leader-follower-based distributed formation flight is designed in such a manner that multiple UAVs cover affected area collectively. The leader is a fixed-wing UAV which deploys multiple rotary-wing UAVs which fly at a fixed altitude and over a specific area that is dedicated to them. Each rotary-wing UAV gathers information and captures images from its under-coverage area, and as a result, the whole affected area is covered by the proposed heterogeneous multi-agent system.

However, comparative study with researches introduced in the literature is addressed in Table 1.

As far as the authors have studied, none of the researches have proposed a heterogenous cooperative multi-UAV system for a two-phase firefighting operation. The main contributions of this paper are summarized as follows:

1) Developing a distributed cooperative coverage control scheme for quickly and initially assessment of the surveillance region by fixed-wing UAVs and extracting critical sections wherein more detailed information gathering is needed.
2) Presenting a distributed cooperative search algorithm using multiple cooperative quadcopters to gather more detailed information in critical sections extracted by fixed-wing UAVs.
3) Proposing a two-phase firefighting operation deploying heterogenous multi-UAV system consisting fixed-wing UAVs and quadcopters.

Table 1 Comparison of the presented scheme with researches studied in the literature

Reference	Year	Objective	Search task (Targets' localization)	Quick scanning (Extracting critical sections)	Hetero-geneous	UAV		UGV
						Fixed wing	Rotary wing	
[10]	2018	Estimate a propagating fire boundary and create an autonomous system that works in real time	×	×	×	✓	×	×
[11]	2018	Design a distributed control structure to monitor fire closely and precisely track its development	×	×	×	×	✓	×
[12]	2019	Use deep reinforcement learning approaches for decentralized control of multiple autonomous fixed-wing aircraft to maximize forest fire coverage and also enable firefighters to make informed controlling decisions	×	×	×	✓	×	×
[13]	2018	Planning trajectory of a fleet of UAVs flying over a wildfire at a leveled altitude and equipped with thermal cameras	×	×	×	✓	×	×
[14]	2022	Obstacle avoidance for a swarm of UAVs in a search and rescue mission	×	×	×	✓	×	×
[15]	2022	Proposing a multi-UAV system for cooperative wildfire coverage and tracking						
[16]	2011	Develop a multi-UAV distributed decisional architecture for sensor deployment, fire confirmation and extinguishing and finally multi-UAV surveillance	×	×	×	×	✓	×
[17]	2021	Multiple multi-rotor UAVs with different capabilities were used to collaboratively detect fire on the ground or on the facade of tall buildings and then try to extinguish the fire by throwing a blanket or spraying water	×	×	✓	×	✓	×
[18]	2010	Formation flight of multiple UAVs for aerial imaging over a disaster area such as wood fire	×	×	×	×	✓	×
[19]	2018	Formulate the consensus-based multi-UAV cooperation problem in a distributed network to monitor the fire development	×	×	×	×	✓	×
[20]	2017	Estimate the wildfire rate of spread, analyze and predict the fire behavior utilizing a cooperative multi-agent system	×	×	×	×	✓	×
[21]	2019	Cover the entire fire zone with a minimum number of drones and minimize the energy consumption and latency of the available drones to fly to the fire zone	×	×	✓	×	✓	×
Our work	2023	1) Proposing a two-phase firefighting operation deploying heterogenous multi-UAV system consisting fixed-wing UAVs and quadcopters. 2) Developing a distributed cooperative coverage control scheme for quickly and initially assessment of the surveillance region by fixed-wing UAVs and extracting critical sections wherein more detailed information gathering is needed. 3) Presenting a distributed cooperative search algorithm using multiple cooperative quadcopters to gather more detailed information in critical sections extracted by fixed-wing UAVs	✓	✓	✓	✓	✓	×

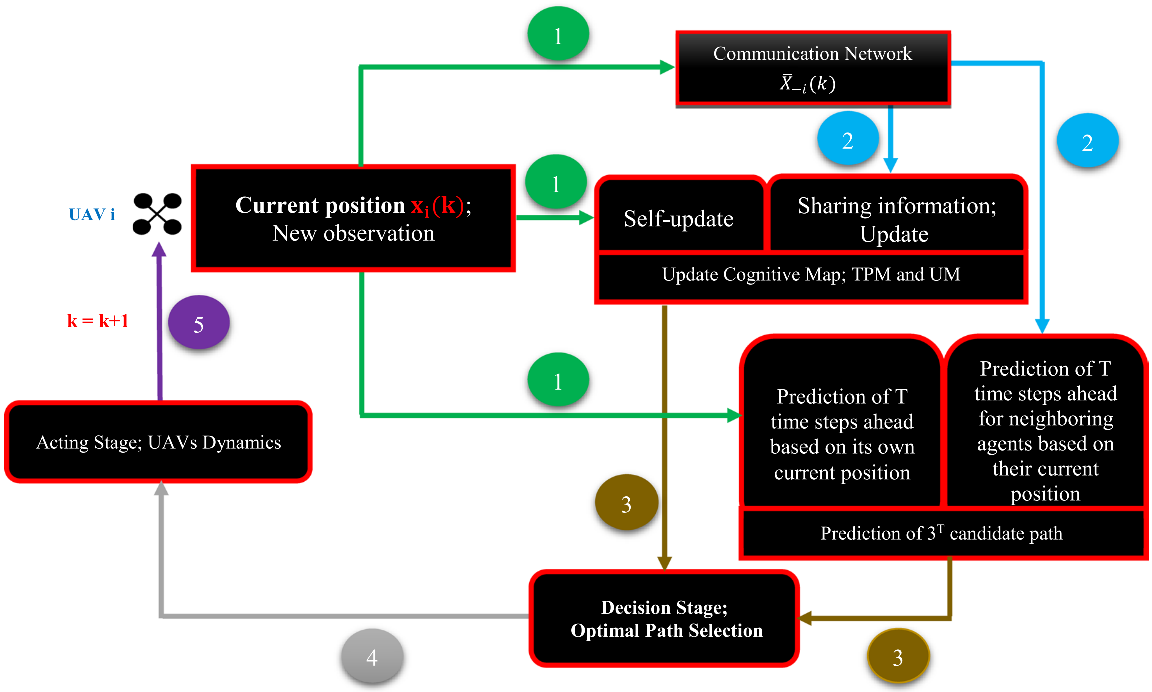


Fig. 1 Steps of the distributed cooperative coverage control scheme for autonomous search task in forest firefighting

In summary, in this paper, we address a cooperative coverage control problem deploying a heterogeneous multi-agent system. In order to prevent the spread of fire, it is very important that the operational team can first have a comprehensive map of the amount of damage and casualties so that based on that they can prioritize and plan for action in more critical sections. For this purpose, we considered a heterogeneous team consisting of multiple fixed-wing UAVs and multiple multi-rotor UAVs. First, the team of fixed-wing UAVs fly over the fire area and along with a general scan of the environment, they produce an initial map that includes critical areas based on the density of human casualties and fire severity. Then, the team of multi-rotor UAVs go to the critical areas, fly at a lower altitude and hover if necessary to extract more detailed information.

The remainder of the paper is structured as follows. In Sect. 3, the distributed receding horizon cooperative search and coverage control problem is formulated. A two-phase firefighting scenario is designed in Sect. 4. In the first phase of the mission, a cooperative team of fixed-wing UAVs are deployed for quick scanning of the surveillance region and extracting critical sections. In the second phase, a cooperative team of multiple quadcopters are used for more detailed information gathering since they are capable of hovering at lower altitudes. Finally, Sect. 5 concludes this work.

3 Problem formulation

Solving the problem of collaborative search and coverage control for various applications of multi-agent systems, especially search and rescue, monitoring, surveillance, information gathering and logistics, would be very effective and helpful. The main goal in the problem of cooperative search and coverage control is to program the movement of agents in such a way that while observing different points of the environment and ensuring maximum coverage, they minimize the uncertainty in knowledge of the multi-agent system about the environment and at the same time localize exactly the targets randomly distributed in the environment [22].

In the cooperative search and coverage control problem, at first none of the agents have any knowledge of the environment, and they gradually increase their knowledge by observing different points of the environment. Agents choose their next path in such a way that they go to points that have not been observed by other agents, and consequently have not been discovered yet, or the probability of the presence of the target in those points of the environment is higher than other points. For this purpose, we used two probability maps, TPM and UM, to build a cognitive map in which TPM is a target probability map and UM is uncertainty map. Figure 1 depicts the steps of the distributed cooperative search and coverage control algorithm which includes five steps as follows:

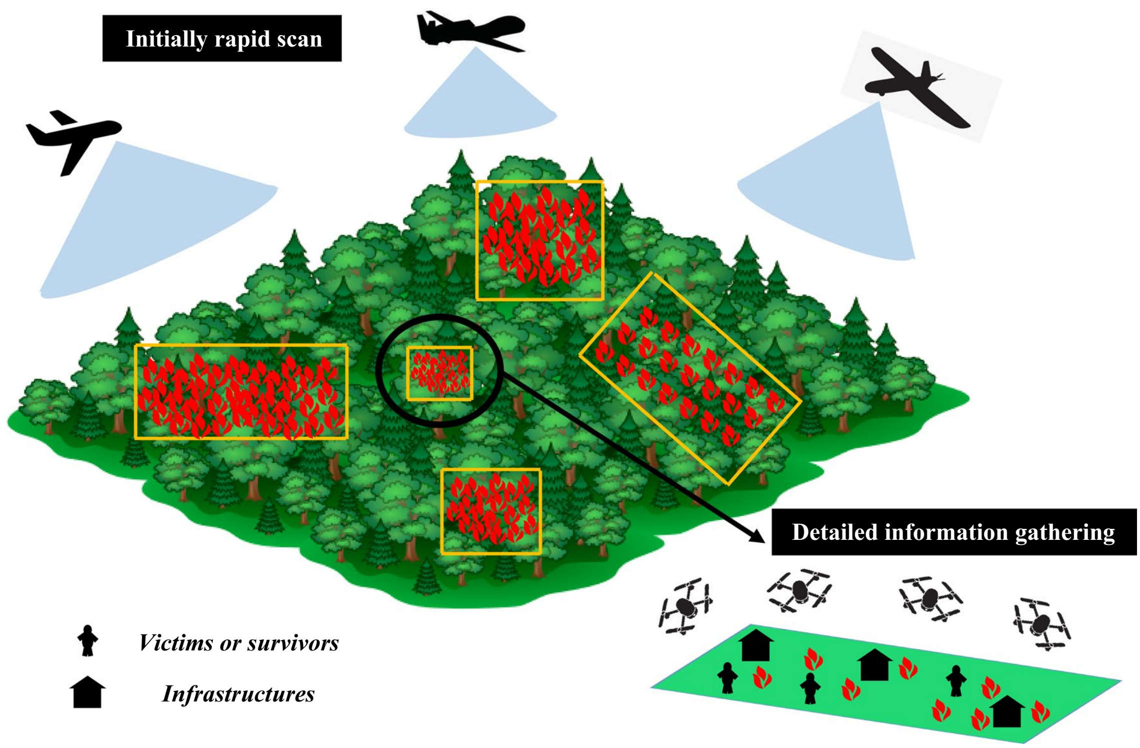


Fig. 2 Heterogeneous cooperative multi-agent system for semi-autonomous firefighting; a cooperative team of fixed-wing UAVs for initially rapid scan and a cooperative team of multirotor UAVs for more detailed information

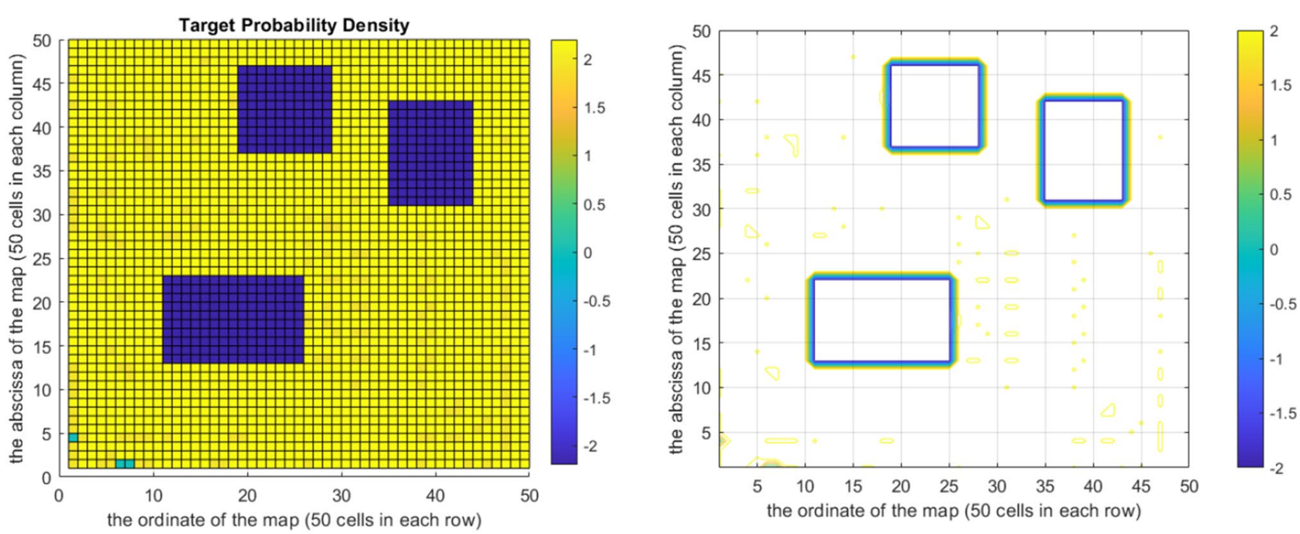


Fig. 3 Target probability map; all three critical areas are detected (TPM approaches to 2.1972 and -2.1792 represent the absence and existence of the target in the cell, respectively)

Step 1:

Each of the agents builds and updates the TPM based on their current position and their observation of the environment according to [23]:

$$p_{i,c,k} = \begin{cases} \frac{p_d p_{i,c,k-1}}{p_d p_{i,c,k-1} + p_f (1-p_{i,c,k-1})}, c \epsilon \mathbb{C}_{i,k} and Z_{i,c,k} = 1 \\ \frac{(1-p_d) p_{i,c,k-1}}{(1-p_d) p_{i,c,k-1} + (1-p_f)(1-p_{i,c,k-1})}, c \epsilon \mathbb{C}_{i,k} and Z_{i,c,k} = 0 \\ p_{i,c,k-1}, c \epsilon \notin \mathbb{C}_{i,k} \end{cases} \quad (1)$$

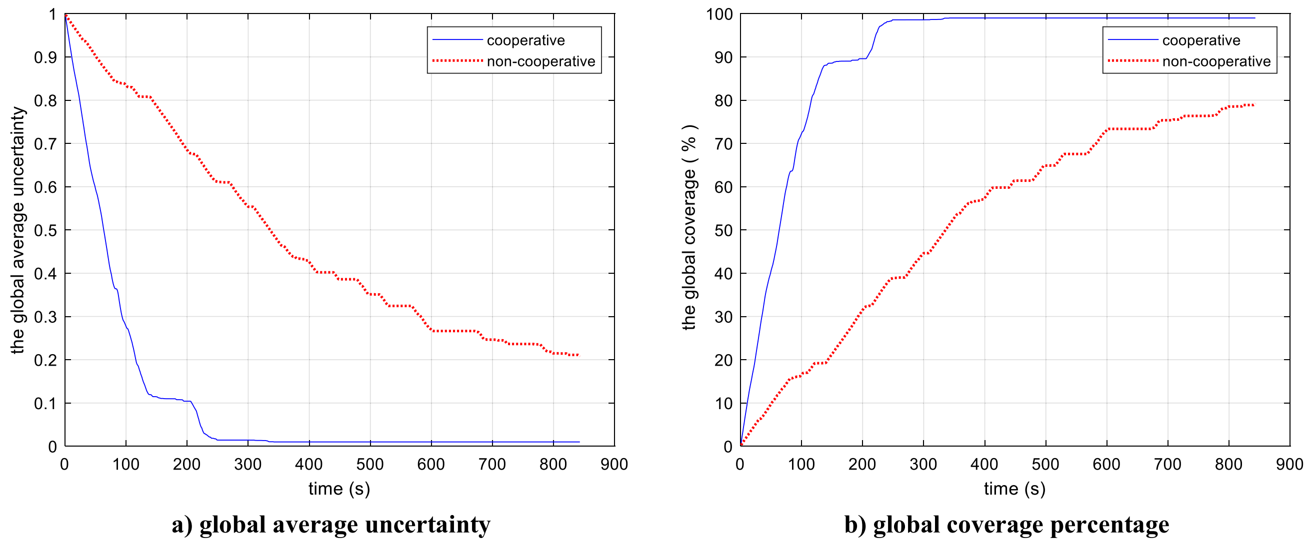


Fig. 4 Comparison of cooperative and non-cooperative coverage control schemes

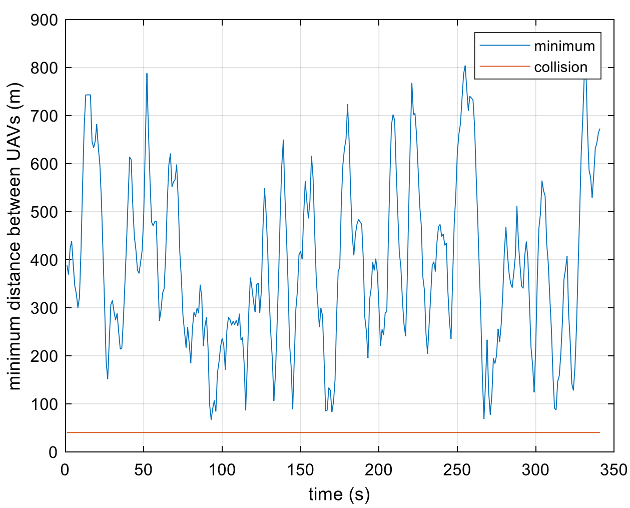


Fig. 5 Collision avoidance of fixed-wing UAVs during their collaborative operation

In which c is the cell number, and $Z_{i,c,k} = 1$ indicates that the agent A_i at time step k has observed the target in cell c and also $Z_{i,c,k} = 0$ means that it believes that there is no target in cell c at time step k according to A_i. Furthermore, $\mathbb{C}_{i,k}$ is the set of cells covered by agent A_i at moment k which is calculated as follows:

$$\mathbb{C}_{i,k} = \left\{c\Omega : \ \alpha_c - \alpha_i(k) \ \le R_s\right\} \tag{2}$$

In which α_c, $\alpha_i(k)$ and R_s are coordinate of tell c, coordinate of the agent A_i's position at time step k and sensing radius of the sensors, respectively, and Ω represents the set of all cells in to which the surveillance region is divided.

Moreover, p_d and p_f the detection and false probabilities which define the sensor performance are as follows:

$$P(Z_{i,c,k} = 1|TE_c = 1) = p_d \& P(Z_{i,c,k} = 1|TE_c = 0) = p_f$$

In which $\mathrm{TE}_c \varepsilon \{0, 1\}$ implies the presence or absence of the target in cell c so that $\mathrm{TE}_c = 1$ and $\mathrm{TE}_c = 0$ indicate that the target is present and absent in the cell c, respectively.

In addition, based on their current positions and dynamic models, they predict their positions up to the next T time steps. Kinematic movement equations of the agents are considered in the following simple way:

$$\begin{aligned} x_i(k+1) &= x_i(k) + v_c.\Delta t.\cos\psi_i(k) \\ y_i(k+1) &= y_i(k) + v_c.\Delta t.\sin\psi_i(k) \end{aligned} \tag{3}$$

In which x_i and y_i are x and y components of the agent A_i's position, v_c is the constant cursing speed, Δt is time step and $\psi_i(k)$ is the heading angle of agent A_i at time step k.

The movement of the agents is assumed to be in 2D x-y plane and at a constant altitude and speed, and so the heading angle is the only input to control the movement of the agents. It is also assumed that each agent has only three options for changing the direction, in other words, it can go straight forward without changing the angle, or it can turn clockwise at an angle of 45 degrees and go forward, or it can turn at an angle of 45 degrees counterclockwise and go forward. Therefore, there are three choices in each time step, and if we want to predict the next T time steps, there will be 3^{T} candidate paths for each agent.

At the same time, they send their current position to the neighboring agents and also receive the current position of the neighboring agents.

Table 2 Description of parameters used in simulation of initial rapid scan of the forest fire deploying four fixed-wing UAVs

Parameter	Value
Initial position of agents	A1: (-620, -980); x and y components in meter
	A2: (-220, -980); x and y components in meter
	A3: (180, -980); x and y components in meter
	A4: (580, -980); x and y components in meter
Constant cruising speed of agents	A1: 70 m/sec
	A2: 75 m/sec
	A3: 80 m/sec
	A4: 85 m/sec
Number of cells the area is divided to	2500
Size of cells	40 m × 40 m
Rc; communication range	4000 m
Rs; sensing radius	60 m
p_d; detection probability	0.9
p_f; false probability	0.3
T_s; time step	0.1 s

Table 3 Description of parameters used in simulation of search task in three critical sections, by a cooperative team of quadcopter UAVs

	Critical Sect. 1	Critical Sect. 2	Critical Sect. 3
Number of cells the area is divided to	2400	1728	2500
Size of cells	10 m × 10 m	10 m × 10 m	8 m × 8 m
R_c; communication range	1000 m	600 m	580 m
R_s; sensing radius	15 m	15 m	12 m
p_d; detection probability	0.9	0.9	0.9
p_f; false probability	0.3	0.3	0.3
T_s; time step	0.1	0.1	0.1

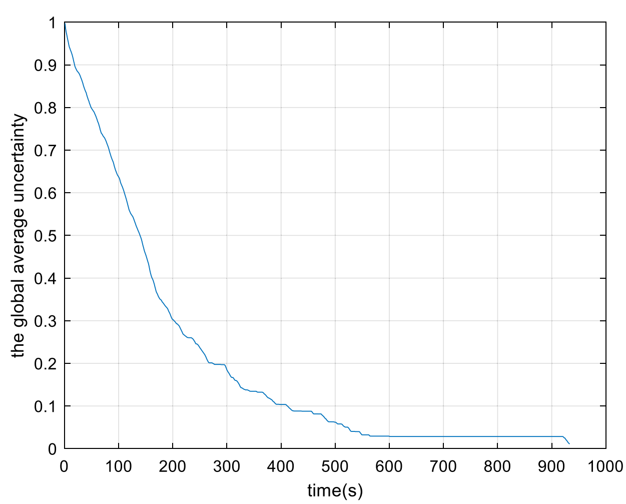


Fig. 6 Global average uncertainty; critical Sect. 1

Step 2

Now, based on the shared information, they update the TPM once again:

$$Q_{i,c,k} = \sum_{j=1}^{N} \omega_{i,j,k} \ln\left(\frac{1}{p_{i,c,k}} - 1\right) \quad (4)$$

$\omega_{i,j,k} = \frac{1}{N_i}$ if j $N_i(k)$ or otherwise $\omega_{i,j,k} = 0$.

In which $N_i(k)$ represents the set of agents that are in the communication range with agent A_i.

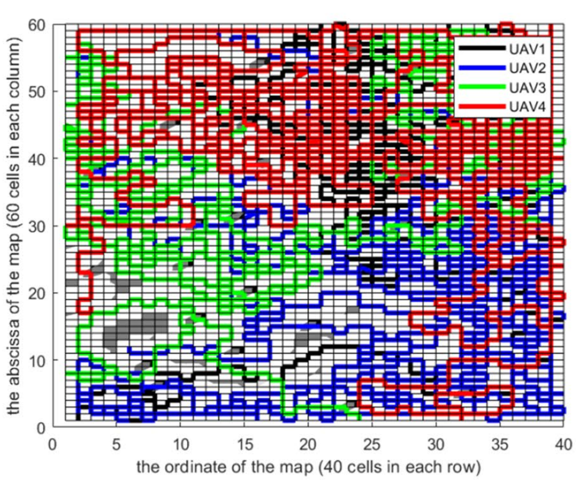
Then, the agents build the UM based on updated TPM:

$$\eta_{i,c,k} = e^{-\vartheta \left| Q_{i,c,k} \right|} \quad (5)$$

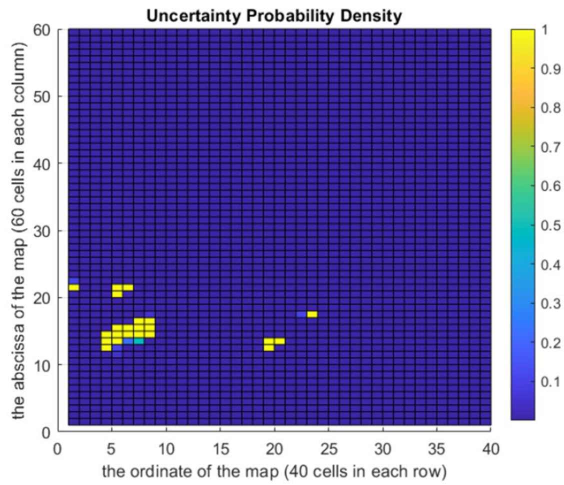
In which ϑ is a positive constant. On the other hand, each of agents predicts neighboring agents' positions up to the next T time steps, based on their current position.

Step 3

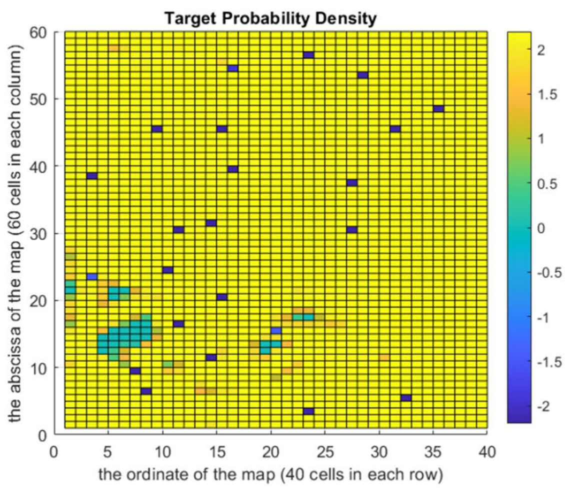
According to its current position and that of its neighbors as well as its next T time steps movement and that of its neighbors, and based on the updated TPM/UM, each agent calculates the optimal path through the following cost function in such a way that while guaranteeing non-collision path, it goes to a point that reduces the uncertainty and

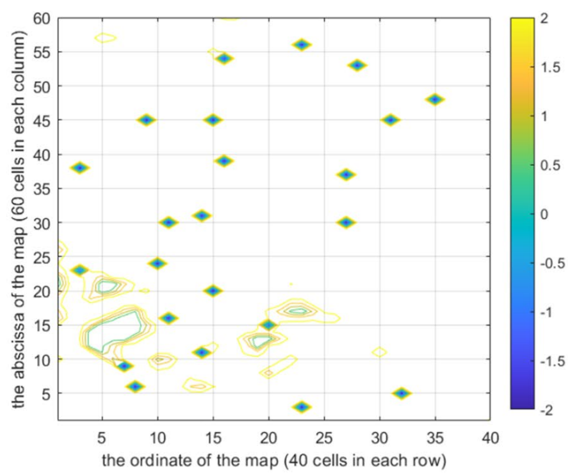


a) UAVs' trajectory and covered cells; t = 932.5 s



b) Uncertainty Map; t = 932.5 s; Uncertainty value equals to 1 means the cell is unknown and equals to 0 means the cell is completely known





c) Target Probability Map; t = 932.5 s; 20 targets with probability of more than 88 %, 1 target with probability of more than 85 % and 2 targets with probability of more than 80 % are detected (TPM approaches to 2.1972 and -2.1792 represents the absence and existence of the target in the cell, respectively)

Fig. 7 Cognitive map and UAVs trajectories at time 932.5 s in critical Sect. 1

increases the probability of identifying the target so that, with the collaboration of other agents, the uncertainty is minimized, and the coverage is maximized finally.

$$J(i,l,k) = \sum_{q=1}^{T} \sum_{c\epsilon\mathbb{C}_i(p_i^l(k+q|k))} \eta_{i,c,k} \tag{6}$$

s.t. $\min(\mathrm{d_{ij}}) \geq \mathrm{d_{collision}}$

In which $J(i,l,k)$, $p_i^l(k+q|k)$ and $\eta_{i,c,k}$ are cost function related to the l'th candidate path of A_i at time step k, target probability according to A_i's observation in the l'th candidate path at time step k + q, based on information up to time step k and uncertainty of cell c according to A_i at time step k, respectively. Moreover, $\mathrm{d_{ij}}$ stands for distance between agents A_i and A_j, and $\mathrm{d_{collision}}$ is the safe distance which ensure the collision-free path.

Step 4

Each agent acts based on the calculated optimal control input and goes to the new point and registers a new observation.

Step 5

The loop is repeated based on the new observation and the new position.

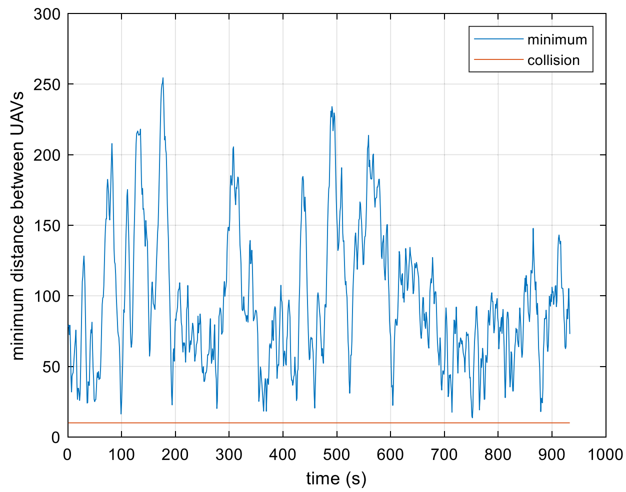


Fig. 8 Collision avoidance of UAVs during their collaborative operation in critical Sect. 1

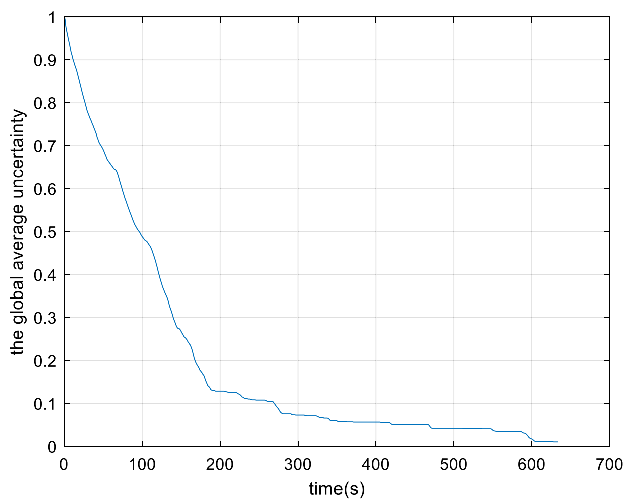


Fig. 9 Global average uncertainty; critical Sect. 2

4 Scenario design and simulation results

As explained in Sect. 2, multi-agent systems can be deployed for several various applications. In this paper, we design a two-phase firefighting scenario as depicted schematically in Fig. 2, considering a heterogeneous multi-agent system to accomplish a search and rescue mission in a forest firefighting operation in which a cooperative team of multiple fixed-wing UAVs scan the affected area and determine the most critical sections with the most economic cost and the most victims, and then, separate multiple cooperative teams of quadcopters will be sent to the most critical regions to gather more detailed information and determine the exact location of the victims or survivors and damaged infrastructures as well. All simulations are conducted in Matlab/Simulink on a Laptop equipped with an Intel(R) Core (TM) i7-9750H CPU @ 2.60 GHz, 16 Gb of RAM memory and a GeForce® GTX 1050 with 4 GB GDDR5.

The disaster management team can then use this information and send rescue team or a cooperative team of multiple UGVs. As another suggestion, quadcopters can be equipped with supplies such as food or drug and drop them for injured people to survive.

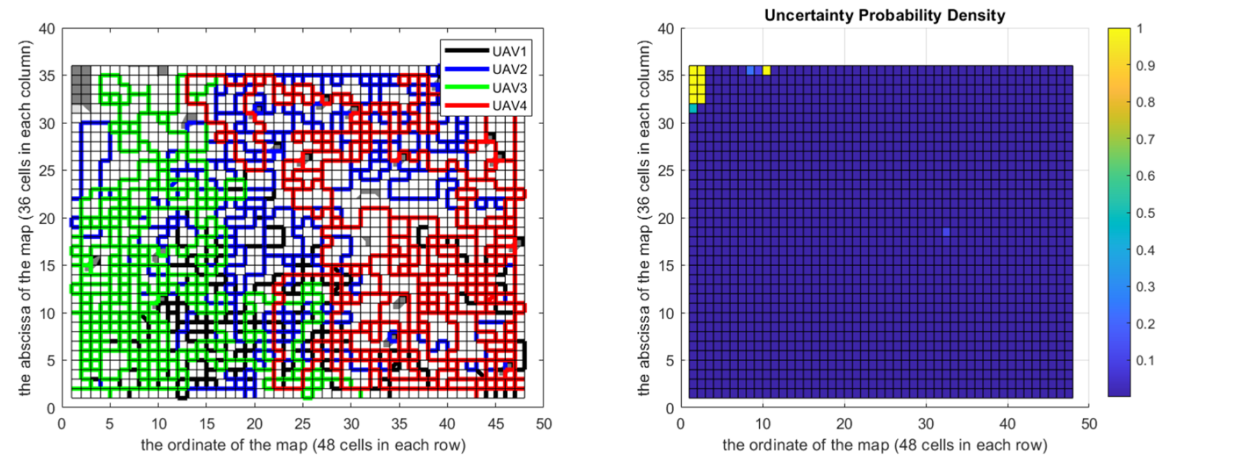
4.1 Phase 1; quickly and initially scanning

In the first phase of the mission, we considered a $2km \times 2km$ surveillance region which has to be explored by a cooperative team of four fixed-wing UAVs. The parameters used for this simulation are listed in Table 1. There are three critical rectangular regions which the cooperative multiple fixed-wing UAVs have to discover for more detailed information gathered by the next cooperative multi-agent systems that comprise quadcopters.

Figure 3 shows the target probability map, TPM, when the global average uncertainty reached 0.1. The probability of the presence of a target in all the cells of the environment. According to each of the agents', observation at the beginning of the mission is equal to 0.5, and gradually when the agents patrol the environment and observe new cells, they update this number. In this way, if there is a target in that cell, the probability of the presence of the target tends to 1 from that agent's point of view, and if there is no target, it tends to 0, and the agent is sure of the presence or absence of the target in that cell, and that cell is no longer uncertain and will be discovered. Thus, over a period of time, uncertainy of the multi-agent system's knowledge about the surveillance region will move from 1 to 0 which means that the area is explored, and maximum ceoverage is acheived.

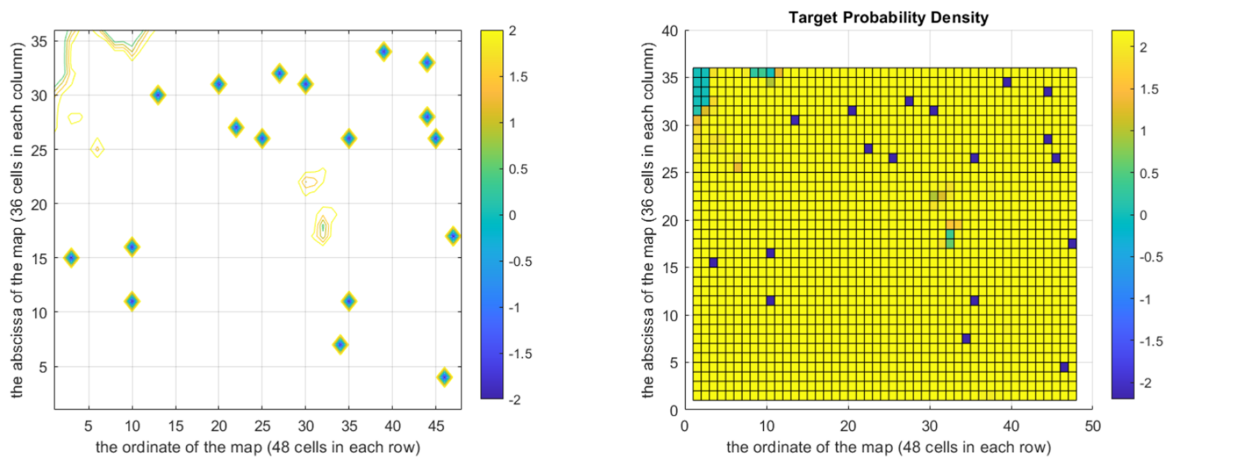
The global average uncertainty and the global coverage percent for both cooperative and non-cooperative TPM update methods are depicted in Fig. 4. As described before, in cooperative scheme, UAVs share information with their neighbors. As shown in Fig. 4, in cooperative scheme, the uncertainty and coverage percentage converge to acceptable minimum and maximum values, respectively, much faster than non-cooperative method.

Figure 5 shows that the collision avoidance is guaranteed as the minimum distance between the UAVs is always more than 40 m, which means that two UAVs are never in the same cell. The blue line is minimum distance among all agents at each time step, and the red line shows the safe distance; if the distance of the agents is less than this value, non-collision path will be ensured.



a) UAVs' trajectory and covered cells; t = 633.9 s

b) Uncertainty Map; t = = 633.9 s; Uncertainty value equals to 1 means the cell is unknown and equals to 0 means the cell is completely known



c) Target Probability Map; t = 633.9 s; all 18 targets are detected and localized with the probability of more than 88 % (TPM approaches to 2.1972 and -2.1792 represents the absence and existence of the target in the cell, respectively)

Fig. 10 Cognitive map and UAVs trajectories at time 253.6 s in critical Sect. 2

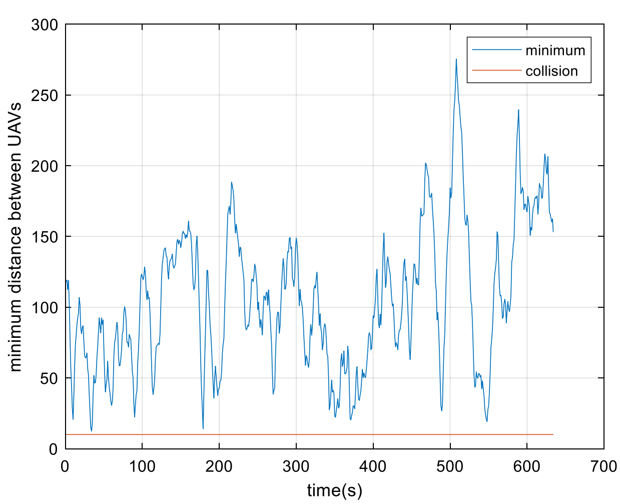


Fig. 11 Collision avoidance of UAVs during their collaborative operation in critical Sect. 2

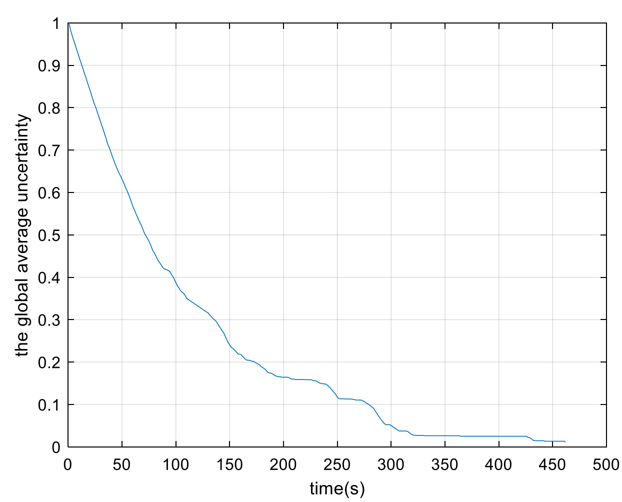
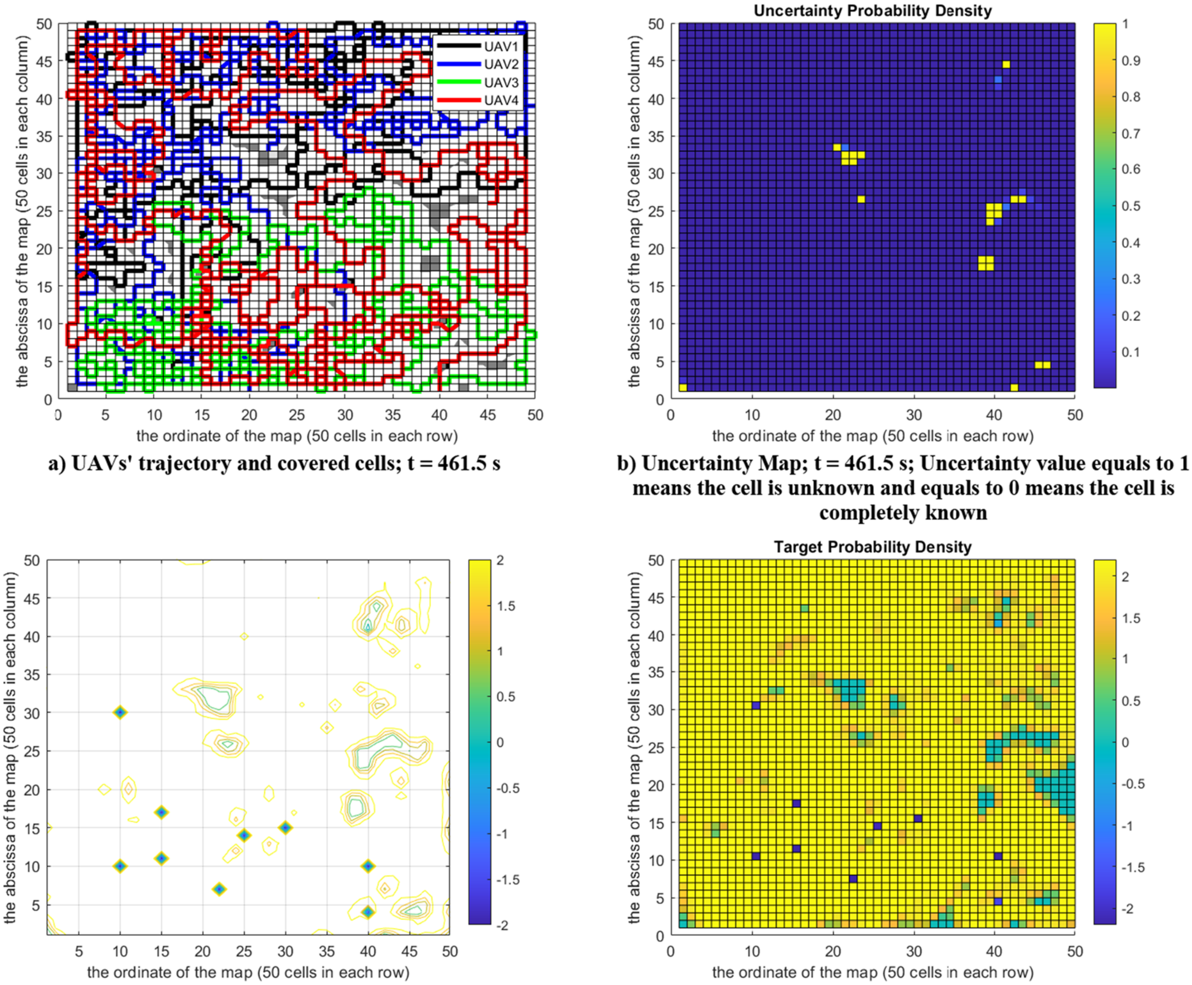


Fig. 12 Global average uncertainty; critical Sect. 3



a) UAVs' trajectory and covered cells; t = 461.5 s

b) Uncertainty Map; t = 461.5 s; Uncertainty value equals to 1 means the cell is unknown and equals to 0 means the cell is completely known

c) Target Probability Map; t = 461.5 s; 8 targets with the probability of more than 88 %, 1 target with the probability of more than 80 % and 1 target with the probability of more than 60 % are detected and localized (TPM approaches to 2.1972 and -2.1792 represents the absence and existence of the target in the cell, respectively)

Fig. 13 Cognitive map and UAVs trajectories at time 461.5 s in critical Sect. 3

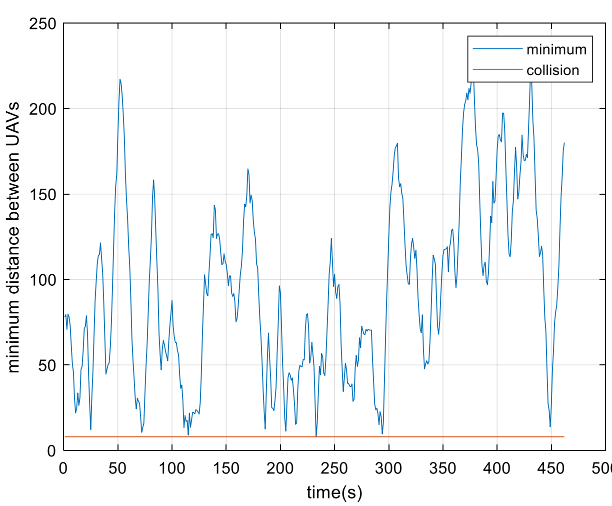


Fig. 14 Collision avoidance of UAVs during their collaborative operation in critical Sect. 3

4.2 Phase 2; more detailed information gathering and cooperative search for targets

When these three critical areas are identified, three separate cooperative multi-agent systems will be sent from the closest UAV stations to gather more detailed information. For each three critical Sects. 1, 2 and 3, we considered four cooperative quadcopters. Sections 1, 2 and 3 are a 400m × 600m, 480m × 360m and 400m × 400m rectangular region, in which there are 23, 18 and 10 targets, respectively, that three separate team of four cooperative quadcopters have to extract their exact locations. Simulation will stop when the global average uncertainty satisfies $\overline{\eta} \leq 0.01$. The detail of the paramters used in these three simulations is listed in Tables 2 and 3.

As it is shown in Fig. 6, the global average uncertainty is 0.01 at time t = 932.5 s. The UAVs trajectories, uncertainty map and target probabbilty map at time t = 932.5 s are depiceted in Fig. 7.

As indicated in Fig. 8, the minimum distance between the UAVs is always more than 10 m which means that the collision avoidance is guaranteed since two UAVs are never in the same cell in the first identified critical section.

The global average uncertainty $\overline{\eta} \leq 0.01$ is satisfied at time t = 633.9 as indicated in Fig. 9. The UAVs trajectories, uncertainty map and target probabbilty map at time t = 633.9 s are depiceted in Fig. 10.

The minimum distance between the UAVs is always more than 10 m as shown in Fig. 11, which guarantees the collision avoidance since two UAVs will never be in the same cell in the second identified critical section.

Figure 12 implies that the global average uncertainty aproaches to 0.01, and the maximum ceverage is achieved at time t = 461.5 s.

The UAVs trajectories, uncertainty map and target probabbilty map at time t = 461.5 s are depiceted in Fig. 13. Every two UAVs will never be in the same cell in the third identified critical section since the minimum distance between the UAVs is always more than 8 m as it is shown in Fig. 14, which guarantees the collision avoidance.

5 Conclusion

In this paper, we presented a distributed predictive control scheme for a cooperative team of heterogeneous UAVs to collaboratively explore a disaster area and search for exact location of probable victims or survivors. The first main contribution of this research is developing a distributed predictive coverage control structure for a cooperative heterogeneous multi-agent system in a firefighting disaster scenario. The UAVs communicate and share information with their neighbors and cooperatively build the cognitive maps including TPM and UM. Based on updated cognitive map, each UAV independently decides about its next movement in such a manner that maximize the coverage and minimize the uncertainty without any collisions collaboratively. Each UAV predicts its possible movements few time steps ahead and neighboring agents' candidate paths as well. Decision structure is such that each agent then solves an optimization problem to choose the optimal path from those candidate paths, based on cognitive map and collision avoidance with neighbors' possible routes. In this scenario, we certified the efficiency and capacity of the multi-UAV system to be deployed by disaster management team for various applications such as monitoring, search and rescue, information gathering and logistics. The second contribution is using heterogeneous multi-agent system in a two-phase mission, comprising fixed-wing UAVs for generally and initially fast scanning of the environment in the first phase of the mission and rotary-wing UAVs to gather more detailed information and localize exactly the probable victims or survivors in the critical sections prioritized by cooperative fixed-wing UAVs, in the second phase of the mission.

In the future work, we will employ the Monte Carlo simulation to assess the effect of the number of UAVs, the sensing radius, the detection and false alarm probabilities and the communication range on the presented scheme and calculate optimal values of each. We also will extend the cooperative search and coverage algorithm for moving targets and also fault-tolerant control. Currently robustness of a multi-agent system to the agents' failure is so challenging. During or after wildfire disaster, failure of one or more agents is highly probable. So it is very important that a coverage control of a multi-agent system be robust to one or more agents' failure. In such case, a fault-tolerant control has to be designed, so the rest of the system is able to accomplish the mission by automatic reconfiguration.

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Declarations

Conflict of interest The authors guarantee that there is no conflict of interest.

Ethical approval This paper is the authors' own original work, which has not been previously published elsewhere. The paper is not currently being considered for publication elsewhere. The paper reflects the authors' own research and analysis in a truthful and complete manner. The results are appropriately placed in the context of prior and existing research. All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference. All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

Consent to participate The authors declare that they voluntarily agreed to participate in this research study.

Consent for publication The authors give their consent for publication of the submitted paper details, which can include photograph(s) and/or tables and/or details within the text ("Material") to be published in the Journal of the Brazilian Society of Mechanical Sciences and Engineering.

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