Optimal Sensor Management for Multiple Target Tracking Using Cooperative Unmanned Aerial Vehicles

Stanley Baek and George York

Abstract— **In this work, we consider collaborative unmanned aerial vehicles (UAVs) with a gimbaled sensor tracking multiple mobile surface targets, where the number of targets is greater than the number of UAVs. To this end, we have developed an efficient distributed software algorithm enabling a team of collaborative unmanned aerial vehicles to effectively detect and track multiple mobile ground targets. The software framework we present in this paper includes optimal sensor management technique to minimize the localization uncertainty of targets, efficient data association method, and a consensus decision-making algorithm to reach agreement on target assignments. Our novel strategy in this integrated framework of cooperative aerial robots effectively utilizes their sensing resources using the optimal sensor management technique as well as the consensus decision-making. Our results show that a team of n UAVs can effectively track more than $2n$ targets with acceptable localization uncertainties.**

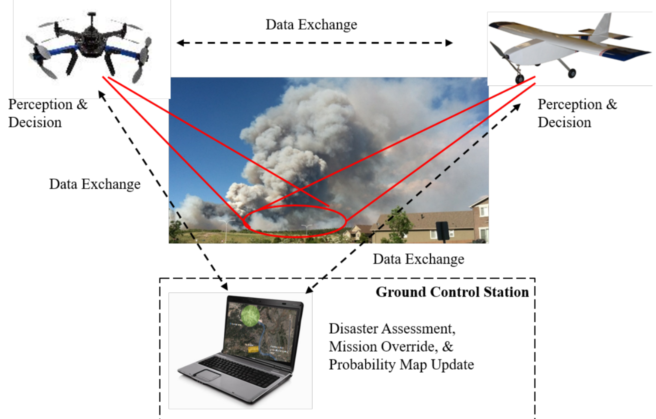

Fig. 1. Conceptual disaster monitoring, detection, tracking, and assessment system based on UAVs

I. Introduction

Early detection and suppression of disasters are imperative to minimize the casualties and destruction that the disasters may cause. Effective detection, monitoring, searching, tracking, and assessment is essential in such missions (Fig. 1 shows a concept). Recently, remote aerial sensing of disaster areas has rapidly become one of the most effectively used tools for monitoring and detection methods [1]. Advances in sensor technologies and computer science have allowed remote sensing systems to provide a promising solution for monitoring and detection of disasters [2]. Furthermore, with their maneuverability and extended operation range, unmanned aerial vehicles (UAVs) equipped with various navigation sensors have great potential for detecting, monitoring, tracking, and assessing disasters.

Over the last few decades, engineers and researchers have made remarkable progress toward the development of unmanned aerial vehicles (UAVs). Such advancements in development of UAVs have led us to a new generation of airborne wireless sensor networks that exhibit a broad range of military and civil applications. Recent examples include intelligence collection, surveillance, reconnaissance [3], environmental monitoring [4], target tracking [5], [6], disaster monitoring and assessment [7]–[9], and search and rescue missions [10], to name a few. For such applications, searching and tracking of multiple surface targets are fundamental and challenging tasks. Since the sensing capabilities of UAVs are constrained by the UAV dynamics, communication link among UAVs, and the onboard sensor dynamics, intelligent path planning for UAVs as well as optimal sensor placement to maximize target localization accuracy is an important area of research.

Tracking of multiple targets has also been studied using various techniques, such as a model predictive control (MPC) [3], [11], [12], a recursive least square filter [13], data association technique [14], and a vision-based algorithm [15]. These techniques represent efforts in the field of autonomous UAVs aiming for search and tracking of multiple mobile targets. Like other counterparts in UAV, geo-localization technologies of ground and water surface targets using UAVs are robust and reliable. These techniques include robust vision-based multiple-target localization without terrain data [16] and optimal nonlinear sensor fusion algorithm with computer vision-based classification methods [17]. Presently, research is focused on optimal search and tracking of multiple mobile target tracking (minimizing uncertainty of target locations) using a team of cooperative UAVs.

Researchers have adopted a probability map in the area of target search and tracking, where the uncertainty of target localization is typically formulated with a grid map. Each cell in the grip map is assigned with a probability value between 0 and 1. Millet *et al.* [18] developed a decentralized method

The authors are with the Department of Electrical and Computer Engineering, United States Air Force Academy, USAF Academy, CO, 80840, USA {stanley.baek, george.york}@usafa.edu

Manuscript 157 submitted to 2020 International Conference on Unmanned Aircraft Systems (ICUAS). Received February 29, 2020.

for a team of multiple UAVs with finite communication range to search for stationary targets, where each individual agent maintained local probability maps. Bourgault *et al.* [19] developed a Bayesian approach to coordinating decentralized sensor networks to maximize the cumulative probability of location of a lost target. This work was extended by Wong *et al.* [20] and Furukawa *et al.* [21] for multiple target search and tracking missions. Later, Bourgault *et al.* [22] adopted more detailed process and observation models to validate the proposed method. The authors in these scenarios employed a recursive Bayesian filter to perform the prediction and update of a probability map, but a priori information of a lost target was assumed known. Bertuccelli and How [23], [24] proposed a new statistical approach that incorporates imprecise knowledge of the prior probabilities in the grid map to generate search actions, where a binary value was assigned to each cell in the grid map based on detection results. Chung *et al.* [25] presented a probabilistic framework for search and identification of multiple targets using a mixed-integer programming and receding horizon technique to maximize the expected number of targets found. Mirzaei *et al.* [26] adopted a Bayesian filter to update a priori probability maps based on the sensor measurements of stationary targets. To solve the coverage problem in this work, they partitioned the entire search region into a Voronoi diagram and employed a dynamic programming method to find the optimal paths. Sun *et al.* [27] developed a strategy to update the probability map for cooperative UAVs that individually store the probability information of dynamic target locations in the search area.

The main contribution of the work presented here is development of a new framework for multiple decentralized flying robots that can manage their sensors to effectively detect and locate multiple mobile targets (for example, propagation of a forest fire, survivors, and rescuers) in uncertain dynamic environments. In particular, our novel strategy determines a target assignment for effective target tracking and updates the target assignment with other cooperative agents using consensus decision-making. This is in sharp contrast to the conventional approach of controlling them separately as each individual problem.

II. Target Tracking and Data Association

The equations of motion of the ground target are given by

$$p_{k+1}^{t,n} = p_k^{t,n} + \Delta T v_k^t \cos\theta_k^t + \frac{1}{2}\Delta T^2 a_k^t \cos\theta_k^t \tag{1a}$$
$$p_{k+1}^{t,e} = p_k^{t,e} + \Delta T v_k^t \sin\theta_k^t + \frac{1}{2}\Delta T^2 a_k^t \sin\theta_k^t \tag{1b}$$
$$v_{k+1}^t = v_k^t + \Delta T a_k^t \tag{1c}$$
$$\theta_{k+1}^t = \theta_k^t + \Delta T \omega_k^t \tag{1d}$$

where $p_k^{t,n}$ and $p_k^{t,e}$ are the discrete-time position of the ground target in the north and east direction, respectively, at time k; v_k^t, θ_k^t, ω_k^t and a_k^t are, respectively the speed, heading, angular velocity, and acceleration of the ground target in the inertial reference frame; and ΔT is the time step. We assume that the angular velocity and the acceleration of the target remain constant for a short period of time, ΔT.

For the optimal localization of the ground targets, we have formulated an unscented Kalman filter (UKF) as follows

$$\mathbf{x}_{k+1}^t = \mathbf{f}(\mathbf{x}_k^t) + \mathbf{w}_k^t \tag{2a}$$
$$\mathbf{z}_k^t = \mathbf{h}(\mathbf{x}_k^t) + \mathbf{v}_k^t \tag{2b}$$

where $\mathbf{x}^t$ is the state vector defined by $\mathbf{x}^t = [p^{t,n}\ p^{t,e}\ v^t\ \theta^t]^\top$; $\mathbf{z}^t$ is the observation vector; $\mathbf{f}$ is the state-transition model, representing the kinematics of the ground target in the discrete time domain; $\mathbf{h}$ is the observation model; $\mathbf{w}_k^t \sim \mathcal{N}(0, Q^t)$ is a zero mean Gaussian random vector with covariance Q_k^t, representing the uncertainties in the system model; and $\mathbf{v}^t \sim \mathcal{N}(0, R^t)$ is a zero mean Gaussian random vector with covariance R^t, representing measurement noise. According to (1), the state-transition model is given by

$$\mathbf{f}(\mathbf{x}_k^t) = \begin{bmatrix} p_k^{t,n} + \Delta T v_k^t \cos\theta_k^t \\ p_k^{t,e} + \Delta T v_k^t \sin\theta_k^t \\ v_k^t \\ \theta_k^t \end{bmatrix} \tag{3}$$

and the observation model, assuming that only position measurements are available, is given by

$$\mathbf{h}(\mathbf{x}_k^t) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \mathbf{x}_k^t \tag{4}$$

The acceleration a_k^t and angular velocity ω_k^t in (1) are unknown in target tracking, and therefore we consider them as unmodeled system uncertainty (or external disturbances). Then, the disturbance in the UKF equations in (2a) are given by

$$\mathbf{w}_k^t = \begin{bmatrix} \frac{1}{2}\Delta T^2 \bar{a} \cos\theta_k^t \\ \frac{1}{2}\Delta T^2 \bar{a} \sin\theta_k^t \\ \Delta T \bar{a} \\ \Delta T \bar{\omega} \end{bmatrix} \tag{5}$$

where $\bar{a}$ and $\bar{\omega}$ are uncorrelated zero mean Gaussian random variables with variance of σ_a^2 and σ_ω^2, respectively. Consequently, the system uncertainty covariance matrix $Q_k^t \in \mathbb{R}^{4\times4}$ can be formulated by $Q_k^t = \mathbb{E}[\mathbf{w}_k^t(\mathbf{w}_k^t)^\top]$, where $\mathbb{E}[\cdot]$ denotes the expectation operator. Finally, the measurement uncertainty covariance matrix, $R^t \in \mathbb{R}^{2\times2}$ can be given by

$$R^t = \begin{bmatrix} (\rho^n)^2 & 0 \\ 0 & (\rho^e)^2 \end{bmatrix} \tag{6}$$

where $(\rho^n)^2$ and $(\rho^e)^2$ are variances of position measurement error of the target in the north and east direction, respectively.

The unscented transformation (UT) is a novel method for calculating the statistics of a random variable which undergoes a nonlinear transformation. A set of points (or sigma points) are chosen so that their sample mean and sample covariance are $\hat{\mathbf{x}}$ and $\mathbf{P}_x$. The nonlinear function is applied to each point in turn to yield a cloud of transformed points, and $\hat{\mathbf{y}}$ and $\mathbf{P}_y$ are the statistics of the transformed points.

The N-dimensional random variable $\mathbf{x}$ with mean $\hat{\mathbf{x}}$ and covariance $\mathbf{P}_x$ is approximated by $2N+1$ weighted points given by

$$\mathcal{X}_0 = \bar{\mathbf{x}} \quad (7)$$

$$\mathcal{X}_i = \bar{\mathbf{x}} + \left(\sqrt{(n+\lambda)\mathbf{P}_\mathbf{x}}\right)_i \quad (8)$$

$$\mathcal{X}_{i+n} = \bar{\mathbf{x}} - \left(\sqrt{(n+\lambda)\mathbf{P}_\mathbf{x}}\right)_i \quad (9)$$

where $i = 1, 2, ..., N$ and $\lambda = \alpha^2(N+\kappa) - N$ is a scaling parameter. The constant α determines the spread of the sigma points around $\bar{\mathbf{x}}$, and is usually set to a small value (e.g., $10^{-4} \leq \alpha \leq 1$). The constant κ is a secondary scaling parameter, which is usually set to $3 - N$ (see [28], [29] for details). $(\sqrt{(n+\lambda)\mathbf{P}_\mathbf{x}})_i$ is the ith column of the matrix square root. These sigma vectors are propagated through the nonlinear function.

$$\mathcal{Y}_i = h(\mathcal{X}_i), i = 0, 1, ..., 2N, \quad (10)$$

and the mean and covariance for (y) are approximated using a weighted sample mean and covariance of the posterior sigma points,

$$\hat{\mathbf{y}} \approx \sum_{i=0}^{2N} \mathcal{W}_i \mathcal{Y}_i, \quad (11)$$

$$\mathbf{P}_\mathbf{y} \approx \sum_{i=0}^{2N} \mathcal{W}_i (\mathcal{Y}_i - \bar{\mathbf{y}})(\mathcal{Y}_i - \bar{\mathbf{y}})^\top, \quad (12)$$

where weights $\mathcal{W}_i$ are given by

$$\mathcal{W}_0 = \frac{\lambda}{N+\lambda}, \quad (13)$$

$$\mathcal{W}_i = \frac{1}{2(N+\lambda)}, i = 1, 2, ...2N. \quad (14)$$

$$(15)$$

The UKF equations are given in Table I for the state space model given in (2a) and (2b). Note that no explicit calculations of Jacobian are necessary to implement this algorithm.

With a number of targets to simultaneously track, it is necessary at each time step to associate the newly arrived measurements with the targets that we have already been tracking. When targets are detected in a search region, each target must be assigned to a UKF to estimate its current location and predict its future locations. The measurement prediction for the j-th track at time k is defined to be $\hat{\mathbf{y}}_k^{j-} = \sum_{i=0}^{2N} \mathcal{W}_i h(\mathcal{X}_k^{j-})$, where $\mathcal{X}_k^{j-}$ is a priori state estimate of the j-th track. Then the measurement residual becomes $v_k^{ij} = \mathbf{y}_k^i - \hat{\mathbf{y}}_k^{j-}$, where $\mathbf{y}_k^i$ is the i-th target in the new measurements. A validation gate can be set up around measurements as follows

$$v_k^{ij} S_k^{-1} (v_k^{ij})^\top \leq g^2, \quad (16)$$

where g^2 is chosen for a confidence level. If the i-th target in the new measurements satisfies (16), the j-th track becomes a candidate for the i-th target to be associated with. If there exist multiple targets that satisfy (16), then the target with

TABLE I

THE UKF ALGORITHM FOR STATE ESTIMATION

Initialize:

$\hat{\mathbf{x}}_0 = E[\mathbf{x}_0]$,

$\hat{\mathbf{P}}_0 = E[(\mathbf{x}_0 - \hat{\mathbf{x}}_0)(\mathbf{x}_0 - \hat{\mathbf{x}}_0)^\top]$.

Compute: For k = 1, 2, ...

$\mathcal{X}_k^- = \left[\hat{\mathbf{x}}_k^-, \quad \hat{\mathbf{x}}_k^- + \sqrt{(L+\lambda)\mathbf{P}_k^-}, \quad \hat{\mathbf{x}}_k^- - \sqrt{(L+\lambda)\mathbf{P}_k^-}\right]$

$\mathcal{X}_k^- = \mathbf{F}(\mathcal{X}_k^-)$

$\hat{\mathbf{x}}_k^- = \sum_{i=0}^{2N} \mathcal{W}_i \mathcal{X}_{i,k}^-$

$\mathbf{P}_k^- = \sum_{i=0}^{2N} \mathcal{W}_i (\mathcal{X}_{i,k}^- - \hat{\mathbf{x}}_k^-)(\mathcal{X}_{i,k}^- - \hat{\mathbf{x}}_\mathbf{k}^-)^\top + \mathbf{Q}_v$

$\mathcal{Y}_k^- = h(\mathcal{X}_k^-)$

$\hat{\mathbf{y}}_k^- = \sum_{i=0}^{2N} \mathcal{W}_i \mathcal{Y}_{i,k}^-$

$\mathbf{S}_{yy} = \sum_{i=0}^{2N} \mathcal{W}_i (\mathcal{Y}_{i,k}^- - \hat{\mathbf{y}}_k^-)(\mathcal{Y}_{i,k}^- - \hat{\mathbf{y}}_k^-)^\top + \mathbf{Q}_u$

$\mathbf{P}_{xy} = \sum_{i=0}^{2N} \mathcal{W}_i (\mathcal{X}_{i,k}^- - \hat{\mathbf{x}}_k^-)(\mathcal{Y}_{i,k}^- - \hat{\mathbf{y}}_k^-)^\top$

$\mathbf{K} = \mathbf{P}_{xy} \mathbf{S}_{yy}^{-1}$

$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}(\mathbf{y}_k - \hat{\mathbf{y}}_k^-)$

$\mathbf{P}_k = \mathbf{P}_k^{-1} - \mathbf{K}\mathbf{P}_{yy}\mathbf{K}^\top$

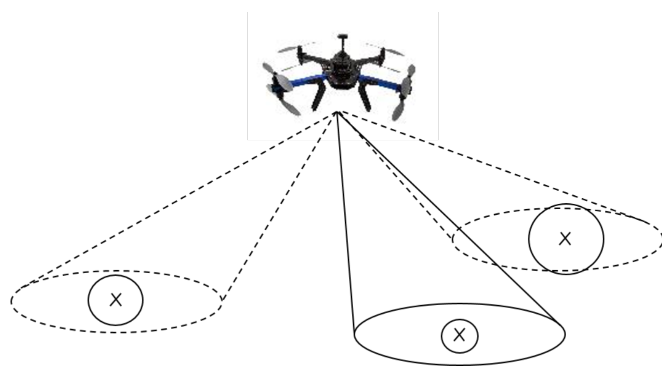

Fig. 2. A UAV is tracking multiple targets using a gimbaled camera. The x symbols represent estimated target location and the circle around the x symbol indicate the localization uncertainty obtained from the state estimate covariance. The solid ellipse indicates the current camera view and the dashed ellipses indicate possible camera views in the future.

the lowest value of $v_k^{ij} S_k^{-1} (v_k^{ij})^\top$ is associated with the j-th track. If there exists no track for a target in the new measurement, we create a new track for the target. If a track cannot find a target to associate for a certain period of time, we consider the track as a stale track and remove it from available tracks.

With a gimbaled camera, a UAV can track multiple targets concurrently as shown in Figure 2. To minimize the overall target localization uncertainty, we need to setup a control policy of the gimbal. First, we calculate a posteriori state covariance matrices for all targets assigned to the UAV (we will discuss target assignment in the following section) with

Manuscript 157 submitted to 2020 International Conference on Unmanned Aircraft Systems (ICUAS). Received February 29, 2020.

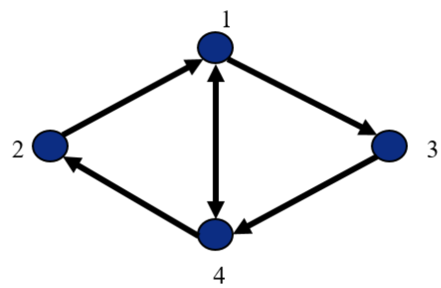

Fig. 3. An example of communication link for 4 cooperative UAVs

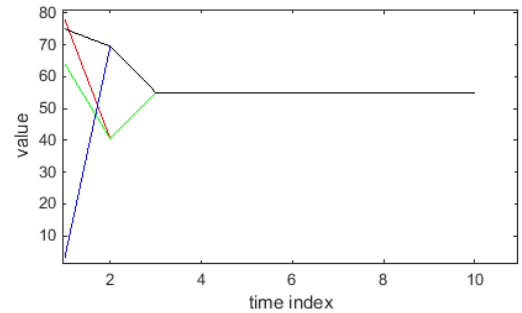

Fig. 4. Four UAVs with different initial values reach a consensus agreement

and without an observation, i.e., we calculate all possible localization uncertainties for all assigned target. The uncertainty of a target location can be easily calculated by taking the trace of a posteriori state covariance matrix of the target. Then, we decide for the next time step which target the gimbaled camera needs to point at in order to minimize the overall uncertainty.

III. Graph Theory and Consensus Algorithm for Target Assignment

With multiple UAVs tracking multiple targets, we need to assign targets to each UAV to maximize the number of tracking targets at any given time. The framework of the target assignment aims at balancing resource usage. A balanced resource usage method can prevent a single UAV from tracking too many targets while other UAVs are performing other tasks, in which case it is more likely to lose targets. Therefore, the target assignment solution in this work is to find a set of UAV-to-target pairings that assigns exactly one UAV to each detected target. However, due to a communication delay and occasionally unreliable communication link, the transmission of state information as well as sensor data may be delayed or lost. Consequently, the UAVs may have different decisions for target assignment. In order to reach a consensus among the UAVs, we have integrated a consensus decision-making algorithm based upon a graph theory.

Communication among cooperative UAVs is modeled using graph theory to describe the communication network [30]. A graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$ consists of a set of node $\mathcal{N} = \{1, \ldots, N\}$ and a set of edges $\mathcal{E} \subseteq \mathcal{N} \times \mathcal{N}$ [31]. If there exists a communication link from node i to node j, then we can say that there is an edge from node i to node j designated by $e_{ij} \triangleq (i, j)$ and node j receives data from node i. The Laplacian matrix $\mathcal{L}$ of a graph $\mathcal{G}$ can describe the connectivities of the nodes in $\mathcal{G}$. The off-diagonal elements of $\mathcal{L}$ are defined by $l_{ij} = -1$ for $i \neq j$, where l_{ij} is the element at the i-th row and the j-th column of $\mathcal{L}$. The diagonal elements of L is simply the negative sum of the off-diagonal elements in the same row or column, which is indeed the number of edges coming in to the designated node. For example, the Laplacian matrix for the graph shown in Figure 3 is written in

$$\mathcal{L} = \begin{bmatrix} 2 & -1 & 0 & -1 \\ 0 & 1 & 0 & -1 \\ -1 & 0 & 1 & 0 \\ -1 & 0 & -1 & 2 \end{bmatrix} \tag{17}$$

We have solved for the target assignment at each UAV based on the distance of the targets from each UAVs then implemented a binary average consensus algorithm [32] to reach consensus decision for the global target-assignment. More specifically, the consensus algorithm exchanges the target assignment solution between neighboring UAVs until the algorithm reaches the average value of UAVs' initial target assignment solution. The target assignment can be represented in a n by m matrix, where n is the number of UAVs and m is the number of targets. If the the element at the i-th row and the j-th column is 1, then the j-th target is assigned to the the i-th UAV. We reshape this matrix into a $n \times m$ by 1 vector and transmit to the neighboring UAVs for consensus agreement. Let $A_j(k)$ be this vector representing the target assignment solution at node j at the time step, k. Then, each UAV updates its own assignment solution with the received information as follows:

$$A_j(k+1) = \delta \left[\frac{1}{|\mathcal{N}_j|} \left(A_j(k) + \sum_{i \in \mathcal{N}_j, i \neq j} A_i(k) \right) \right] \tag{18}$$

where $\mathcal{N}_j$ is the set of neighboring nodes that can communicate with node j including itself, $|\mathcal{N}_j|$ is the number of elements in $\mathcal{N}_j$, and $\delta(\dot{})$ denotes the decision function such that $\delta(x) = 1$ if $x \geq 0.5$ and $\delta(x) = 0$ otherwise.

IV. Experiments and Results

The efficiency of the consensus method we developed has been evaluated with a number of connectivity configurations. Figure 4 shows that four cooperative UAVs connected by the Laplacian matrix given by (17) reach a consensus agreement. In this experiment, we assigned distinct initial values for each agents, i.e., $A_1 = 78$, $A_2 = 3$, $A_3 = 64$, $A_4 = 75$. At the time step of $k = 3$, they have reached an agreement of the value of 56. Although the performance of consensus algorithms highly depends on the connectivity and the number of nodes in the graph, this simple experiment shows the

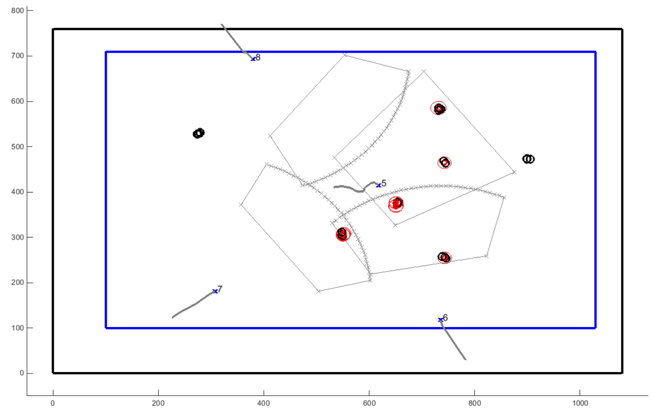

Fig. 5. A simulation snapshot of search and tracking of 7 mobile targets (small circles in black) using 4 UAVs (x marks in blue with gray footprints). The gray quadrilaterals and quadrilaterals with an arc represent sensor exposure areas. The red circles around the targets represent the uncertainty of the targets. The targets without red circle represent undiscovered targets.

TABLE II

PARAMETERS USED IN EXPERIMENTS

target speed	0 - 10 m/s
maximum UAV speed	5 m/s
camera measurement noise variance (σ_r^2)	8
system uncertainty variance (σ_a^2)	1
confidence lever (g^2)	0.95

consensus algorithm we developed is a viable method for cooperative operations of small group of unmanned aerial vehicles.

Figure 5 demonstrates a computer simulation of distributed cooperative search and tracking of ground mobile targets using a team of four UAVs. There are 7 mobile targets with various random movements following random walk, circular, figure eight, cycloidal or sinusoidal path in the mission area (represented in a black rectangle). It shows UAVs are tracking 5 targets (black circles surrounded by red circles) and two targets have not been detected (black circles without red circles). Although the goal of target assignment is to assign exactly one UAV to each detected target, there are two targets simultaneously exposed to two UAVs. It occasionally happens when targets are too close to each other and they are exposed to multiple UAVs.

We performed experiments with various number of targets to verify the performance of our algorithm. The parameters we used for the experiments are described in Table 1. Depending on the target path, the target speeds may vary over time, e.g., the target following the cycloidal path has a speed ranging from 0 to 10 m/s while the target following the circular path has a constant speed.

Figure 6 shows experimental results for 4 UAVs tracking 4 targets for 20 seconds. The overall target uncertainty has been calculated by the sum of traces of a posteriori state estimate covariance matrix of all the target being tracked. The target uncertainty is exponentially decaying until it

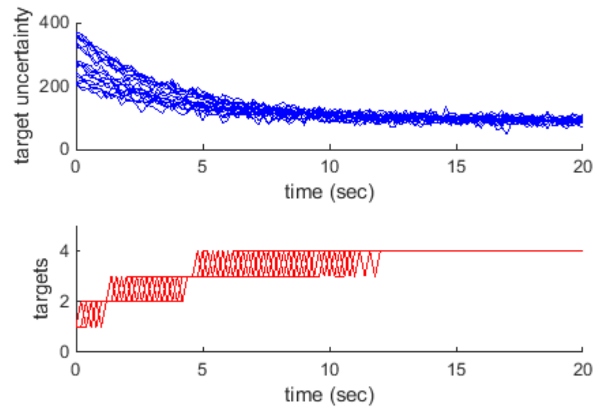

Fig. 6. Experiment of 4 UAVs tracking 4 targets. (top) target uncertainty is the sum of traces of a posteriori state covariance matrix for all targets under tracking. (bottom) the number of targets being tracked.

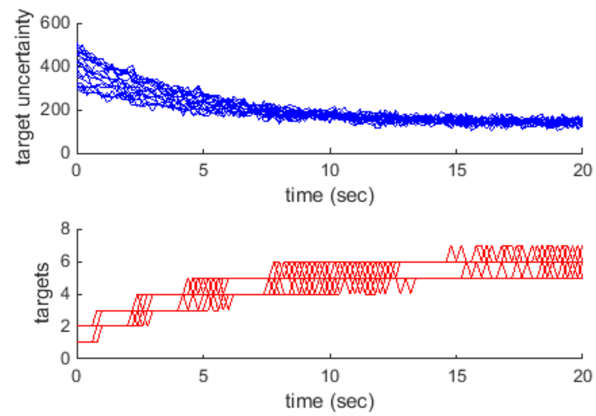

Fig. 7. Experiment of 4 UAVs tracking 7 targets. (top) target uncertainty is the sum of traces of a posteriori state covariance matrix for all targets under tracking. (bottom) the number of targets being tracked.

reaches a steady state value bounded in a small range[1]. The number of target being tracked is initially one or two because one of the UAVs is initially at the center of the mission area and it always detects one or two targets at the beginning. All four targets are being tracked at the end, indicating that each target is assigned to only one UAV through the consensus decision-making algorithm. Once each target is assigned to one UAV, the UAVs can follow the target while their gimbaled camera is pointing at the target.

Shown in Figure 7 are the experimental results for 4 UAVs tracking 7 targets for 20 seconds. The target uncertainty is exponentially decaying until it reaches a steady state value. Not all seven targets are being tracked at the end, indicating that a UAV occasionally fails tracking multiple targets. It is indeed possible when one target travels to the opposite direction of the other target.

Experimental results for 4 UAVs tracking 15 targets for

[1]Although the steady state value cannot be constant due to the measurement noise from the camera, it can be considered to be bounded in a small range.

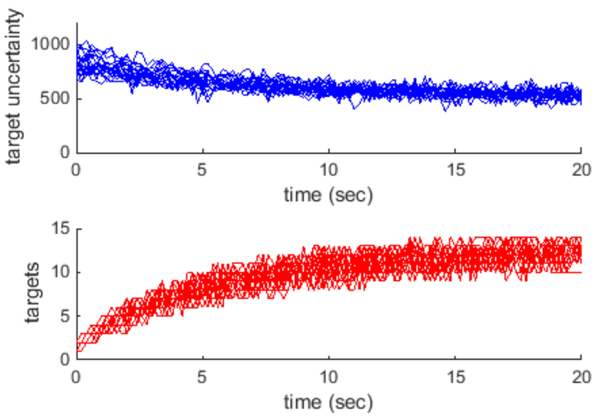

Fig. 8. Experiment of 4 UAVs tracking 15 targets. (top) target uncertainty is the sum of traces of a posteriori state covariance matrix for all targets under tracking. (bottom) the number of targets being tracked.

20 seconds are shown in Figure 8. The target uncertainty is also exponentially decaying until it reaches a steady state value (Note that the scale of the y axis is different than the other experiments). The number of targets being tracked never reaches 15, showing that there is a practical number of target that can be tracked by a certain number of UAVs. In case of 4 UAVs with the parameters shown in Table 1, the maximum number of targets would be 10 or less.

V. Conclusions

We have developed an integrated software framework of cooperative aerial robots that can effectively utilize their sensing using optimal sensor management technique as well as consensus decision-making. The experimental results show that a team of cooperative UAVs with the consensus algorithm can always track the same number of targets without losing a target. Furthermore, the experiments show that a team of n UAVs can effectively track more than 2n targets. The algorithms we developed are computationally inexpensive so that they can be run on lightweight onboard computer units for drones. The new framework we have developed will advance collaborative capabilities of practical aerial robots when they encounter novel situations including cooperative resource management The approach in this work will be applicable and lead to a new class of collaborative robots that will be able to leverage optimal sensor management for multiple heterogeneous tasks. It has the potential for cooperative drones to significantly reduce the casualties in disasters through rapid responses in search and rescue missions in disaster areas.

References

[1] R. Chisholm, J. Cui, S. Lum, and B. Chen, "UAV LiDAR for below-canopy forest survey," *Journal of Unmanned Vehicle Systems*, vol. 1, no. 1, pp. 61–68, 2013.

[2] V. Vipin, "Image processing based forest fire detection," *Emerging technology and advanced engineering*, vol. 33, pp. 173–175, 2012.

[3] N. Farmani, L. Sun, and D. Pack, "Tracking multiple mobile targets using cooperative unmanned aerial vehicles," in *2015 International Conference on Unmanned Aircraft Systems (ICUAS)*, Denver, CO, June 2015, pp. 395–400.

[4] P. Corke, T. Wark, R. Jurdak, W. Hu, P. Valencia, and D. Moore, "Environmental wireless sensor networks," *Proceedings of the IEEE*, vol. 98, no. 11, pp. 1903–1917, Nov 2010.

[5] G. K. Atia, V. V. Veeravalli, and J. A. Fuemmeler, "Sensor scheduling for energy-efficient target tracking in sensor networks," *IEEE Transactions on Signal Processing*, vol. 59, no. 10, pp. 4923–4937, Oct 2011.

[6] H. Cheng, G. Su, and J. Huang, "A distributed cross-layer framework for target tracking in three-dimensional wireless sensor networks," in *Future Wireless Networks and Information Systems*, Y. Zhang, Ed. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 653–661.

[7] D. W. Casbeer, D. B. Kingston, R. W. Beard, and T. W. McLain, "Cooperative forest fire surveillance using a team of small unmanned air vehicles," *International Journal of Systems Science*, vol. 37, no. 6, pp. 351–360, 2006. [Online]. Available: https://doi.org/10.1080/00207720500438480

[8] A. Ollero, J. R. Martinez-Dedios, and L. Merino, "Unmanned aerial vehicles as tools for forest-fire fighting," *Forest Ecology and Management*, vol. 234, no. 1, p. 263, 2006.

[9] L. Merino, J. R. Martínez-de Dios, and A. Ollero, *Cooperative Unmanned Aerial Systems for Fire Detection, Monitoring, and Extinguishing*. Dordrecht: Springer Netherlands, 2015, pp. 2693–2722. [Online]. Available: https://doi.org/10.1007/978-90-481-9707-1_74

[10] A. N. Chaves, P. S. Cugnasca, and J. Jose, "Adaptive search control applied to search and rescue operations using unmanned aerial vehicles (UAVs)," *IEEE Latin America Transactions*, vol. 12, no. 7, pp. 1278–1283, Oct 2014.

[11] N. Farmani, L. Sun, and D. Pack, "Optimal UAV sensor management and path planning for tracking multiple mobile targets," in *Dynamic Systems and Control Conference*, San Antonio, TX, Oct. 2014. [Online]. Available: https://doi.org/10.1115/DSCC2014-6232

[12] R. Sharma and D. Pack, "Cooperative sensor resource management to aid multi target geolocalization using a team of small fixed-wing unmanned aerial vehicles," in *AIAA Guidance, Navigation, and Control (GNC) Conference*, Boston, MA, 2013. [Online]. Available: https://arc.aiaa.org/doi/abs/10.2514/6.2013-4706

[13] J. D. Redding, T. W. McLain, R. W. Beard, and C. N. Taylor, "Vision-based target localization from a fixed-wing miniature air vehicle," in *2006 American Control Conference*, Minneapolis, MN, June 2006, pp. 2862–2867.

[14] S. Oh, L. Schenato, P. Chen, and S. Sastry, "Tracking and coordination of multiple agents using sensor networks: System design, algorithms and experiments," *Proceedings of the IEEE*, vol. 95, no. 1, pp. 234–254, Jan 2007.

[15] L. Ma, C. Cao, N. Hovakimyan, V. Dobrokhodov, and I. Kaminer, "Adaptive vision-based guidance law with guaranteed performance bounds," *Journal of Guidance, Control, and Dynamics*, vol. 33, no. 3, pp. 834–852, 2010. [Online]. Available: https://doi.org/10.2514/1.46287

[16] K. Han and G. N. DeSouza, "Multiple targets geolocation using SIFT and stereo vision on airborne video sequences," in *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct 2009, pp. 5327–5332.

[17] Y. Yoon, S. Gruber, L. Krakow, and D. Pack, "Autonomous target detection and localization using cooperative unmanned aerial vehicles," in *Optimization and Cooperative Control Strategies*, M. J. Hirsch, C. W. Commander, P. M. Pardalos, and R. Murphey, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, pp. 195–205.

[18] T. Millet, D. Casbeer, T. Mercker, and J. Bishop, "Multi-agent decentralized search of a probability map with communication constraints," in *AIAA Guidance, Navigation, and Control Conference*, Toronto, Ontario, August 2010, pp. 1–12. [Online]. Available: https://arc.aiaa.org/doi/abs/10.2514/6.2010-8424

[19] F. Bourgault, T. Furukawa, and H. F. Durrant-Whyte, "Coordinated decentralized search for a lost target in a Bayesian world," in *Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003)*, vol. 1, Las Vegas, NV, Oct 2003, pp. 48–53 vol.1.

[20] El-Mane Wong, F. Bourgault, and T. Furukawa, "Multi-vehicle Bayesian search for multiple lost targets," in *Proceedings of the 2005 IEEE International Conference on Robotics and Automation*, Barcelona, Spain, April 2005, pp. 3169–3174.

Manuscript 157 submitted to 2020 International Conference on Unmanned Aircraft Systems (ICUAS). Received February 29, 2020.

[21] T. Furukawa, F. Bourgault, B. Lavis, and H. F. Durrant-Whyte, "Recursive Bayesian search-and-tracking using coordinated UAVs for lost targets," in *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, Orlando, FL, May 2006, pp. 2521–2526.

[22] F. Bourgault, T. Furukawa, and H. F. Durrant-Whyte, *Optimal Search for a Lost Target in a Bayesian World*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2006, pp. 209–222. [Online]. Available: https://doi.org/10.1007/10991459_21

[23] L. F. Bertuccelli and J. P. How, "Robust UAV search for environments with imprecise probability maps," in *Proceedings of the 44th IEEE Conference on Decision and Control*, Dec 2005, pp. 5680–5685.

[24] ——, "Search for dynamic targets with uncertain probability maps," in *2006 American Control Conference*, Minneapolis, MN, June 2006, pp. 737–742.

[25] T. H. Chung, M. Kress, and J. O. Royset, "Probabilistic search optimization and mission assignment for heterogeneous autonomous agents," in *2009 IEEE International Conference on Robotics and Automation*, Kobe, Japan, May 2009, pp. 939–945.

[26] M. Mirzaei, F. Sharifi, B. W. Gordon, C. A. Rabbath, and Y. M. Zhang, "Cooperative multi-vehicle search and coverage problem in uncertain environments," in *2011 50th IEEE Conference on Decision and Control and European Control Conference*, Orlando, FL, Dec 2011, pp. 4140–4145.

[27] L. Sun, S. Baek, and D. Pack, *Distributed Probabilistic Search and Tracking of Agile Mobile Ground Targets Using a Network of Unmanned Aerial Vehicles*. Cham: Springer International Publishing, 2014, pp. 301–319. [Online]. Available: https://doi.org/10.1007/978-3-319-10807-0_14

[28] S. J. Julier, J. K. Uhlmann, and H. F. Durrant-Whyte, "A new approach for filtering nonlinear systems," in *Proceedings of 1995 American Control Conference - ACC'95*, vol. 3, Seattle, WA, June 1995, pp. 1628–1632.

[29] S. J. Julier and J. K. Uhlmann, "New extension of the Kalman filter to nonlinear systems," in *Signal Processing, Sensor Fusion, and Target Recognition VI*, I. Kadar, Ed., vol. 3068, International Society for Optics and Photonics. Orlando, FL: SPIE, 1997, pp. 182 – 193. [Online]. Available: https://doi.org/10.1117/12.280797

[30] T. A. Severson and D. A. Paley, "Distributed multitarget search and track assignment with consensus-based coordination," *IEEE Sensors Journal*, vol. 15, no. 2, pp. 864–875, Feb 2015.

[31] R. Olfati-Saber, J. A. Fax, and R. M. Murray, "Consensus and cooperation in networked multi-agent systems," *Proceedings of the IEEE*, vol. 95, no. 1, pp. 215–233, Jan 2007.

[32] Y. Mostofi and Ye Yuan, "Impact of heterogeneous link qualities and network connectivity on binary consensus," in *2009 American Control Conference*, St. Louis, MO, June 2009, pp. 1821–1826.

Manuscript 157 submitted to 2020 International Conference on Unmanned Aircraft Systems (ICUAS). Received February 29, 2020.