Distributed Object Tracking Based on Information Weighted UAV Selection with Priory Objects

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***Abstract*—In this work, we propose a distributed cubature information filter based multi-object tracking method with an information weighted selection for unmanned aerial vehicle (UAV) networks. In an UAV network, multiple UAVs can observe multiple objects in the region of interest. Further, the UAVs can exchange the objects local information among themselves and fuse them together to obtain the global state of the objects. As the number of UAVs in the network increases, the information exchange among the UAVs suffers from scalability, bandwidth and energy limitations. Thus, it is usually desirable to allow only a desired number of UAVs with highly relevant information to participate in the information exchange. In our approach, the innovation vector within the information filtering framework is used to calculate the amount of information associated with each UAV. Further, a threshold based selection mechanism is proposed to facilitate the UAVs to take independent decisions on whether to participate in the information exchange or not. In the proposed method, the UAVs take the decision to participate in the information exchange based on the information associated with a dynamic subset of objects known as priory objects while keeping the total number of information exchanges in the network to a desired number (on average).**

I. Introduction

Vision based object tracking with an unmanned aerial vehicle (UAV) is an important feature in several modern applications such as surveillance, disaster management, traffic management, and so on [1]. In these applications, the UAV is equipped with a camera to obtain the visual information of objects in the region of interest (ROI) which can be used to track the objects over time. In [2], [3] and references there in, authors employed the Bayesian filters such as the Kalman filter (KF) and the extended Kalman filter (EKF) to track the objects using a single UAV. The accuracy of single UAV based object tracking algorithms may suffer from different adverse effects such as distance, speed or orientation of the UAV with respect to the objects, occlusions in the ROI, and so on. However, a network of UAVs with overlapping field of views (FOVs) is capable of providing multiple visual measurements of the same object simultaneously. Thereby, aggregating them to achieve a global state can improve the accuracy of the object tracking.

In [4], [5], [6] and [7] authors presented cooperative vision based object tracking methods with multiple UAVs based on the KF, EKF, particle filters and sigma point information filter, respectively. Information filters are more suitable for multi-sensor (UAV) object tracking compared to the conventional Bayesian filters due to their inherent information fusion mechanism [8]. In our previous work [9] and [10], we have proposed a multi-camera object tracking method based on the cubature information filter (CIF) with fixed cameras. There, it is shown that the CIF achieves better tracking accuracy than the extended information filter (EIF). Hence, as one of the key contributions of this paper, the CIF based object tracking is extended for object tracking applications in the UAV networks.

In addition, nowadays, UAV networks tend to evolve into large scale Ad-Hoc networks with limited bandwidth and energy reservoirs [1]. Even though, the large number of UAVs improves the tracking accuracy, the exchange of local information among the UAVs can increase the communication overhead and energy consumption. Hence, allowing only a desired number of UAVs to participate in the information exchange is a way to meet the bandwidth and energy requirements. In [11], authors presented a controlled gossip mechanism for target recognition in swarm UAV networks to match the available resources. In [4], a collaborative tracking method where cameras on the UAVs are directed to point of interest with the necessary adjustments according to the UAV/target movement is proposed to minimize the data transmitted between UAVs. These methods require exchange of control information among the UAVs and/or base stations to select the UAVs that can participate in the information exchange.

In this work, a distributed information weighted UAV selection mechanism that selects on average a desired number of UAVs to participate in the information exchange without any control overhead is proposed. Consider a distributed network of UAVs without a base station that can monitor multiple objects in the ROI simultaneously. Each UAV in the network is equipped with a local CIF in order to calculate the local information metrics for each object in the ROI. In general, the measurements associated with an object in the ROI have a varying degree of information. The proposed method selects on average a desired number of UAVs with highly informative measurements to improve the tracking accuracy. The innovation vector within the CIF framework is used to calculate the amount of information associated with each UAV. The other key features of the proposed method include: i) Each UAV can independently decide whether to participate in the information exchange or not based on the information associated with a subset of objects known as priory objects; ii) Each UAV can have a different set of priority objects; iii) The contribution of each UAV to the desired average transmissions in the network can be different or same while keeping the number of information exchanges in the network to a desired number. Finally, each UAV fuses the information received from

ISBN 978-0-9928626-7-1

the selected UAVs by using the inherent fusion mechanism of the CIF to achieve the global state of the objects in the ROI.

The paper is organized as follows, Section II describes the motion and measurement models of the objects and the UAVs, respectively. Section III describes the basic concepts of information filtering. Section IV explains the proposed information weighted selection mechanism. Section V evaluates the proposed multi-UAV information filtering scheme based on simulation results. Section VI presents the conclusions.

II. SYSTEM MODEL

Let us consider a distributed network consisting of a set of UAVs n_i, where $i = 1, 2, \cdots, N$, that can observe a ROI on the ground plane. The task of the object tracker is to identify and track multiple objects o_j, where $j = 1, 2 \cdots, O$ in the ROI. This is achieved by the CIF based filtering and distributed information fusion performed by each UAV n_i in the network. The state of an object o_j comprises of its position and the velocity in x and y directions on the ground plane. Thus, at time k, the state of the object o_j is described as $\mathbf{x}_{j,k} = [x_{j,k}\ y_{j,k}\ \dot{x}_{j,k}\ \dot{y}_{j,k}]^T$. The motion model of the object o_j at time k is given as

$$\begin{aligned}\mathbf{x}_{j,k} &= \mathbf{f}_{j,k}\left(\mathbf{x}_{j,k-1}, \mathbf{w}_{j,k}\right)\\ &= \begin{bmatrix} x_{j,k-1} + \delta\dot{x}_{j,k-1} + \frac{\delta^2}{2}\ddot{x}_{j,k} \\ y_{j,k-1} + \delta\dot{y}_{j,k-1} + \frac{\delta^2}{2}\ddot{y}_{j,k} \\ \dot{x}_{j,k-1} + \delta\ddot{x}_{j,k} \\ \dot{x}_{j,k-1} + \delta\ddot{y}_{j,k} \end{bmatrix},\end{aligned} \tag{1}$$

where $\ddot{x}_{j,k}$ and $\ddot{y}_{j,k}$ are the accelerations of the object o_j in x and y directions that are modeled by a vector of independent and identically distributed (IID) white Gaussian random variable $\mathbf{w}_{j,k}$ with covariance $\mathbf{Q}_{j,k}$. δ is the time interval between the two consecutive measurements. The state of the object o_j is estimated based on the visual measurements from the UAVs taken at each time step k. The measurements of the object o_j at the UAV n_i and time k are given as

$$\mathbf{z}_{i,j,k} = \mathbf{h}_{i,j,k}\left(\mathbf{x}_{j,k}\right) + \mathbf{v}_{i,j,k}, \tag{2}$$

where $\mathbf{v}_{i,j,k}$ is an IID white Gaussian measurement noise vector with covariance $\mathbf{R}_{i,j,k}$. The measurement function $\mathbf{h}_{i,j,k}$ is the non-linear homography function which converts the object's 3D coordinates on the ground plane to 2D coordinates on the image plane. The homography of the UAV n_i is a function of its rotation matrix $\widetilde{\mathbf{R}}_{i,j,k}$ and position $\mathbf{t}_{i,j,k}$ and camera calibration matrix $\mathbf{K}_{i,j,k}$. The homography matrix $\mathbf{H}_{i,j,k}$ which defines the non-linear homography function in (2) is given as

$$\mathbf{H}_{i,j,k} = \mathbf{K}_{i,j,k}\begin{bmatrix}\widetilde{\mathbf{R}}_{i,j,k} & \mathbf{t}_{i,j,k}\end{bmatrix}. \tag{3}$$

The measurement model (2) is adopted from [7] and [13].

III. THE INFORMATION FILTER FRAME WORK

Information filters are alternative version of the Bayesian filters such as the KF and EKF. In information filtering, the information vector and information matrix are computed and propagated over time k instead of the estimated state vector and error covariance matrix. Let us assume that the initial probability density function (PDF) $p\left(\mathbf{x}_{i,j,0}\right)$ of the object o_j at the UAV n_i is Gaussian with mean $\widehat{\mathbf{x}}_{i,j,0|0}$ and covariance $\mathbf{P}_{i,j,0|0}$. At the UAV n_i and time $k-1$, the estimated global information matrix $\mathbf{Y}_{i,j,k-1|k-1}$ and information vector $\widehat{\mathbf{y}}_{i,j,k-1|k-1}$ of the object o_j are given as

$$\mathbf{Y}_{i,j,k-1|k-1} = \mathbf{P}^{-1}_{i,j,k-1|k-1}, \tag{4}$$

$$\widehat{\mathbf{y}}_{i,j,k-1|k-1} = \mathbf{Y}_{i,j,k-1|k-1}\widehat{\mathbf{x}}_{i,j,k-1|k-1}, \tag{5}$$

where $\widehat{\mathbf{x}}_{i,j,k-1|k-1}$ and $\mathbf{P}_{i,j,k-1|k-1}$ are the estimated global state vector and covariance matrix, respectively.

At time k, information filters have two essential steps: time and measurement update. In the time update, the predicted information matrix and vector $\left[\mathbf{Y}_{i,j,k|k-1}, \widehat{\mathbf{y}}_{i,j,k|k-1}\right]$ are computed from the prior information matrix and vector $\left[\mathbf{Y}_{i,j,k-1|k-1}, \widehat{\mathbf{y}}_{i,j,k-1|k-1}\right]$. Upon receiving the measurement $\mathbf{z}_{i,j,k}$, the measurement update is performed to calculate the information contribution vector and matrix $[\mathbf{i}_{i,j,k}, \mathbf{I}_{i,j,k}]$ as

$$\mathbf{i}_{i,j,k} = \mathbf{A}_{i,j,k}\left(\mathbf{e}_{i,j,k} + \mathbf{P}^T_{\mathbf{xz},i,j,k}\widehat{\mathbf{y}}_{i,j,k|k-1}\right), \tag{6}$$

$$\mathbf{I}_{i,j,k} = \mathbf{A}_{i,j,k}\mathbf{P}^T_{\mathbf{xz},i,j,k}\mathbf{Y}^T_{i,j,k|k-1}, \tag{7}$$

where

$$\mathbf{A}_{i,j,k} = \mathbf{Y}_{i,j,k|k-1}\mathbf{P}_{\mathbf{xz},i,j,k}\mathbf{R}^{-1}_{i,j,k}, \tag{8}$$

and $\mathbf{P}_{\mathbf{xz},i,j,k}$ and $\mathbf{e}_{i,j,k}$ are the cross covariance and innovation vector, respectively. The innovation vector $\mathbf{e}_{i,j,k}$ is given as

$$\mathbf{e}_{i,j,k} = \mathbf{z}_{i,j,k} - \widehat{\mathbf{z}}_{i,j,k|k-1}, \tag{9}$$

where $\widehat{\mathbf{z}}_{i,j,k|k-1}$ is the predicted measurement.

In [9], we illustrated that the CIF can achieve better tracking accuracy than the EIF. Hence, in this paper, the CIF is used as the local information filter at each UAV in the network. Algorithm 1 shows the essential steps of the information filter for each object o_j at the UAV n_i and time k. Refer to [9] for the detailed derivation of the CIF algorithm.

Now, assume that at time k, the UAV n_i receives the local information contribution vectors $\mathbf{i}_{i',j,k}$ and information contribution matrices $\mathbf{I}_{i',j,k}$ from the N' other UAVs in the network. Then, the global information vector and matrix of the object o_j at the UAV n_i and time k are calculated as

$$\widehat{\mathbf{y}}_{i,j,k|k} = \widehat{\mathbf{y}}_{i,j,k|k-1} + \mathbf{i}_{i,j,k}, + \sum_{i'=1}^{N'}\mathbf{i}_{i',j,k}, \tag{10}$$

$$\mathbf{Y}_{i,j,k|k} = \widehat{\mathbf{Y}}_{i,j,k|k-1} + \mathbf{I}_{i,j,k} + \sum_{i'=1}^{N'}\mathbf{I}_{i',j,k}. \tag{11}$$

Algorithm 1 Information filter framework for object o_j at UAV the n_i and time k.

1) Calculate the predicted information vector $\widehat{\mathbf{y}}_{i,j,k|k-1}$
2) Calculate the predicted information matrix $\mathbf{Y}_{i,j,k|k-1}$
3) Calculate the predicted measurement $\widehat{\mathbf{z}}_{i,j,k|k-1}$
4) Calculate the innovation vector $\mathbf{e}_{i,j,k}$
5) Calculate the predicted cross covariance $\mathbf{P}_{\mathbf{xz},i,j,k}$
6) Calculate the information contribution vector $\mathbf{i}_{i,j,k}$
7) Calculate the information contribution matrix $\mathbf{I}_{i,j,k}$

IV. The Information Weighted UAV Selection with Priory Objects

The large scale UAV networks such as the swarm UAV networks can have limited bandwidth and energy reservoirs. Therefore, it is necessary to reduce the number of information exchanges among the UAVs to a desired number while estimating the global information vector and matrix. On the other hand, reducing the information exchanges among the UAVs can lead to decreased tracking accuracy. A better tracking accuracy can be achieved by selecting the desired number UAVs with the highly informative measurements rather than a random selection.

In information filtering, the innovation vector $\mathbf{e}_{i,j,k}$ is the disagreement between the predicted measurement $\widehat{\mathbf{z}}_{i,j,k|k-1}$ and the actual measurement $\mathbf{z}_{i,j,k}$ as shown in (9). The predicted measurement $\widehat{\mathbf{z}}_{i,j,k|k-1}$ is approximated as the expectation of the likelihood PDF $p\left(\mathbf{z}_{i,j,k} \mid \mathbf{x}_{i,j,k|k-1}\right)$. Hence, the innovation $\mathbf{e}_{i,j,k}$ gives the additional information in the received measurement $\mathbf{z}_{i,j,k}$ that is not available in the predicted state $\widehat{\mathbf{x}}_{i,j,k|k-1}$. Hence, the innovation $\mathbf{e}_{i,j,k}$ can be used to quantize the amount of new information available in the measurement $\mathbf{z}_{i,j,k}$ of the object o_j at UAV n_i and time k.

Considering the described system model (1) and (2), the PDF $p\left(\mathbf{e}_{i,j,k}\right)$ of the innovation $\mathbf{e}_{i,j,k}$ of the object o_j at UAV n_i and time k becomes approximately a zero mean Gaussian distributed random variable with covariance $\mathbf{P}_{\mathbf{zz},i,j,k}$. Hence, the information available in the innovation vector $\mathbf{e}_{i,j,k}$ can be calculated using the self information principle [12] as

$$H_{i,j,k} = -\log_e\left(p\left(\mathbf{e}_{i,j,k}\right)\right) \approx \mathbf{e}_{i,j,k}^T \mathbf{P}_{zz,i,j,k}^{-1} \mathbf{e}_{i,j,k} = \chi_{n_z}^2, \quad (12)$$

where $\chi_{n_z}^2$ is a chi-square distribution with a degree of freedom of n_z and n_z is the length of the measurement vector $\mathbf{z}_{i,j,k}$. If the length of the measurement vector remains the same for the object o_j at each UAV n_i, then the information metric $H_{i,j,k}$ at each UAV n_i becomes a chi-square distributed variable with a degree of freedom of n_z irrespective of the corresponding innovation covariance $\mathbf{P}_{\mathbf{zz},i,j,k}$.

The goal of this paper is to select on average a desired number of UAVs based on the amount of information associated with the measurements of a set of priority objects. The priority objects at the UAV n_i are represented with a set $O_{s,i}$ and the number of priority objects is S_i where $S_i \leq O$. Since the innovation vector of the each priority object is independent from each other, we can write

$$p\left(\mathbf{e}_{i,1,k}, \mathbf{e}_{i,2,k}, \cdots, \mathbf{e}_{i,S_i,k}\right) = \prod_{j'=1}^{S_i} p\left(\mathbf{e}_{i,j',k}\right). \quad (13)$$

From (12) and (13), the total information available in the innovation vectors $\mathbf{e}_{i,j',k}$ of the priority objects o'_j where $o'_j \in O_{s,i}$ can be calculated as

$$\begin{aligned} H_{i,S_i,k} &= -\log_e\left(\prod_{j'=1}^{S_i} p\left(\mathbf{e}_{i,j',k}\right)\right) = -\sum_{j'=1}^{S_i} \log_e p\left(\mathbf{e}_{i,j',k}\right), \\ &\approx \sum_{j'=1}^{S_i} \mathbf{e}_{i,j',k}^T \mathbf{P}_{zz,i,j',k}^{-1} \mathbf{e}_{i,j',k} = \sum_{j'=1}^{S_i} H_{i,j',k} = \chi_{Sn_{i,z}}^2, \end{aligned} \quad (14)$$

where $\chi_{Sn_{i,z}}^2$ is a chi-square distribution with a degree of freedom of $Sn_{i,z}$ and $Sn_{i,z}$ is the product of the number of the priority objects S_i and the length of the measurement vector n_z of each priority object. The information metric $H_{i,S_i,k}$ at the UAV n_i indicates the additional new information in the measurements of the priority objects. Subsequently, it can be used by the UAV n_i to decide whether to distribute its local information in the network or not. In order to achieve this objective, we define a threshold $\chi_{i,k}$ to which the priority information metric $H_{i,S_i,k}$ can be compared in such way that at each time k, on average a desired number of UAVs L distribute their local information in the network.

Let us consider an indication element $s_{i,k}$, where $i \in 1, 2, \cdots, N$, that is 1 if the UAV n_i distribute the local information and 0 otherwise.

$$s_{i,k} = \begin{cases} 1 & H_{i,S_i,k} \geq \chi_{i,k} \\ 0 & \text{Otherwise} \end{cases} \quad (15)$$

The goal is to select on average L UAVs to distribute the local information in the network. Thus, from (15), we can write

$$\begin{aligned} \mathbf{E}\left[\sum_{i=1}^{N} s_{i,k}\right] &= \sum_{i=1}^{N} \mathbf{E}\left[s_{i,k}\right] = \sum_{i=1}^{N} \Pr\left(s_{i,k} = 1\right) \\ &= \sum_{i=1}^{N} \Pr\left(H_{i,S_i,k} \geq \chi_{i,k}\right) = L. \end{aligned} \quad (16)$$

Based on (14), the priority information metric $H_{i,S_i,k}$ at any UAV n_i in the network is a chi-square distributed variable with a degree of freedom $Sn_{i,z}$. Hence, if the probability that the information metric $H_{i,S_i,k}$ of the UAV n_i is greater than or equal to the threshold $\chi_{i,k}$ is given as

$$\Pr\left(H_{i,S_i,k} \geq \chi_{i,k}\right) = a_i \frac{L}{N}, \quad (17)$$

where $\sum_{i=1}^{N} a_i = N$, then the average number of information exchanges in the network are limited to L. If the contribution parameter $a_i = 1$ where $i = 1, 2, \cdots, N$, then all the UAVs in the network have the equal probability to transmit their local information. Since the number of UAVs N and the priory objects S in the network and the average number of desired UAVs that can distribute the local information in the network L are known, From (17), the threshold $\chi_{i,k}$ can be calculated as the critical value for which the cumulative probability of chi-square distributed variable $\chi_{Sn_{i,z}}^2$ is greater than or equal to $a_i \frac{L}{N}$ as

$$\chi_{i,k} = \mathbf{F}_{\chi_{Sn_z}^2}^{-1}\left(1 - a_i \frac{L}{N}\right). \quad (18)$$

Each UAV n_i can calculate the threshold $\chi_{i,k}$ at time k and decide whether to distribute their local information in the network or not by comparing the corresponding priority information metric $H_{i,S_i,k}$ with it. Moreover, each UAV n_i can have a different set of priority objects and the average number of transmissions from each UAV can be different or the same depending on its contribution parameter while keeping the number of transmissions in the network to the desired number L. Hence, each UAV in the network runs a local CIF to calculate local information contribution vectors $\mathbf{i}_{i,j,k}$, and information contribution matrices $\mathbf{I}_{i,j,k}$ for each object. Then, all UAVs decide whether to participate in the

ISBN 978-0-9928626-7-1 © EURASIP 2017

information exchange or not by using the proposed information weighted UAV selection method. The estimated global information vector and matrix of each object o_j at the UAV n_i and time k can be achieved by fusing the information distributed in the network as shown in (4) and (5). Algorithm 2 shows the essential steps of the information weighted UAV selection based distributed object tracking algorithm for each object o_j where $j = 1, 2 \cdots, O$ at the UAV n_i where $i = 1, 2 \cdots, N$ and time k.

Algorithm 2 Information weighted UAV selection based distributed object tracking algorithm at UAV n_i and time k

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1) Select S number of priority objects
2) Calculate the threshold $\chi_{i,k}$ as shown in (18)
3) Initialize the priority information metric $H_{i,S_i,k}$ to 0
4) **For** each object o_j, where $j = 1$ to O, perform steps 1 to 7 in Algorithm 1
5) **For** each priority objects $o'_j \in O_s$
   a) Calculate the innovation covariance matrix $\mathbf{P}_{zz,i,j',k}$ as shown in Appendix
   b) Calculate the corresponding information metric $H_{i,j',k}$ as shown in (12)
   c) Add information metric $H_{i,j',k}$ to priority information metric $H_{i,S_i,k}$
6) **If** $(H_{i,S_i,k} \geq \chi_{i,k})$, then distribute $[\mathbf{i}_{i,j,k}, \mathbf{I}_{i,j,k}]$ of all objects o_j, where $j = 1$ to O in the network
7) Compute the global estimated information vector and matrix $\left[\widehat{\mathbf{y}}_{i,j,k|k}, \widehat{\mathbf{y}}_{i,j,k|k}\right]$ for all objects (4) and (5)

V. Simulation Results

In this section, the proposed information weighted UAV selection method is evaluated based on the simulation. In our approach, the tracking accuracy is defined in terms of the sum of the root mean square errors (RMSE) of the estimated global state and the ground truth of the objects in x and y directions. The bandwidth efficiency is calculated in terms of the number of information exchanges in the UAV network. All the UAVs in the network can observe the xy-plane, where x $\in [0, 500]$ m and y $\in [0, 500]$ m. The number of objects in the ROI is considered to be 5. The ground truth of the position of each object is simulated using the motion model given in (1). The process noise covariance $\mathbf{Q}_{i,j,k}$ of the ground truth of the object is considered to be $(5, 5)$. To achieve statistical reliability, the proposed method is evaluated on 100 different trajectories for each object with different initializations. The UAVs are considered to be flying with a fixed altitude and pitch on flat ground plane with different initial points. The yaw angle and the roll of the each UAV are modeled as constant with zero mean Gaussian noise which will define the rotation matrix $\widetilde{\mathbf{R}}_{i,j,k}$ for each UAV n_i. For the simulation purpose, the elements in the camera calibration matrix $\mathbf{K}_{i,j,k}$ of the UAV n_i are generated as Gaussian randoms variable with variance 0.1. The position of the UAV $\mathbf{t}_{i,j,k}$ from time $k-1$ to k are modeled with constant velocity. The homography matrix $\mathbf{H}_{i,j,k}$ at the UAV n_i and time k is then defined as a function rotation matrix $\widetilde{\mathbf{R}}_{i,j,k}$, position of the UAV $\mathbf{t}_{i,j,k}$ and camera calibration matrix $\mathbf{K}_{i,j,k}$ as shown in (3). The measurements at each object at the UAV n_i and time are simulated by assuming that the measurement noise covariance $\mathbf{R}_{i,j,k} = \text{diag}\{0.5, 0.5\}$.

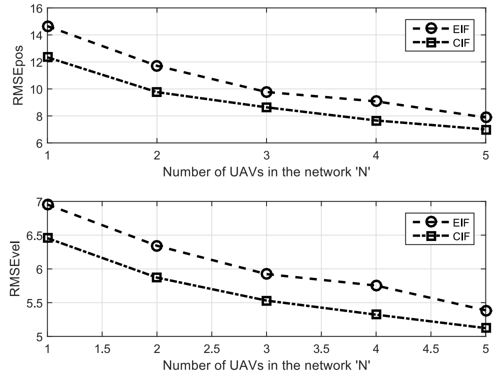

Fig. 1. The RMSE of the estimated position and velocity of the object based on the CIF and EIF object tracking methods compared to the ground truth. The number of UAVs varies from 1 to 5.

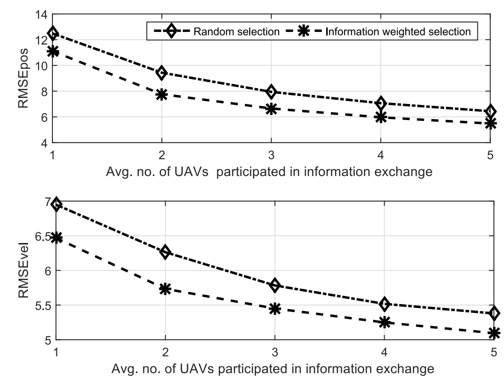

Fig. 2. The RMSE of the estimated position and velocity the CIF based information weighted and random selection methods. The size N of the network is 20. The desired number of UAVs that can participate in the information exchange varies form 1 to 5. The RMSE is averaged over all the 5 objects.

The first part of this section compares the tracking accuracy of the CIF and EIF based methods. For this comparison, only one object is considered in the ROI. Figure 1 shows the RMSE of the estimated position and the velocity of the object over 100 different trajectories compared to the ground truth for varying number of UAVs in the network. The information weighted selection is not employed for this comparison. This figure clearly shows that CIF based distributed object tracking has better estimation accuracy than the EIF based method.

In the second part, the accuracy of the proposed information weighted UAV selection with the priory objects is compared with the random selection. In the random selection, a random subset of L number of UAVs in the network participate in the information exchange independently of the information contained in their measurements. Moreover, the UAVs take independent decisions on whether to participate in the information exchange or not. For this comparison, the number of UAVs in the network is considered to be 20. All the UAVs in the network have the CIF as local on-board filter. To make the comparison fair, we consider all the 5 objects in the ROI as priory objects. In the proposed information weighted selection, the parameter a_i normalized by $N = 20$ is selected as 0.025, 0.0625, 0.075, 0.05 and 0.0375 for $i = 1$ to 4, $i = 5$

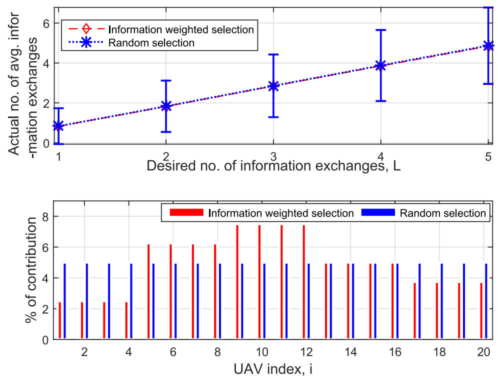

Fig. 3. The average number of information exchanges ± variance in the network and the contribution of each UAV for both the information weighted and random selection methods. The size N of the network is 20. The desired number of UAVs that can participate in the information exchange varies form 1 to 5.

to 8, $i = 9$ to 12, $i = 13$ to 16 and $i = 17$ to 20, respectively.

Fig. 2 shows the RMSE of the estimated position and velocity of distributed object tracking with random selection and the proposed information weighted selection. The x-axis of the figure represents the average number of UAVs that participated in the information exchange at each time k. From this figure, we can infer that the tracking accuracy of both the methods improves with the increasing number of information exchanges. However, the proposed information weighted selection method outperforms the random selection method for any give number of average information exchanges in the network.

Fig. 3 shows the mean ± variance of the number of UAVs that participated in the information exchange in both the information weighted and random selection methods at each time k. The x-axis shows the actual desired number of UAVs L which is used to calculate the threshold as in (18). The y-axis shows the average number of UAVs that participated in the information exchange during the tracking process. In this figure, it is illustrated that on average, the number of UAVs that distributed the local information in the network in both the methods is approximately equal and matches to the theoretical requirements. Fig. 3 also shows the contribution of each UAV to the average number of transmissions in the network. In the random selection method, each UAV has equal contribution to the average transmissions. In the proposed method, the contribution parameter of each UAV can be selected in such a way that the UAVs in the network can have varying contribution to the average transmissions. Hence, from Fig. 2 and Fig. 3, it can be understand that the proposed information weighted UAV selection shows better tracking accuracy than the random selection for the same number of average information exchanges in the network.

VI. Conclusion

In this work, a distributed information weighted UAV selection mechanism is proposed for object tracking applications in the UAV networks. The proposed threshold based selection method selects UAVs with highly informative measurements to participate in the information exchange. The threshold is calculated in such a way that on average only a desired number of UAVs is selected to distribute their local information in the network at each time. Moreover, the UAVs in the network can independently decide to participate in the information exchange only if the information associated with all or a subset objects (priority objects) in the ROI is greater than the threshold. Under the considered simulation, the proposed information weighted UAV selection shows a considerable improvement in tracking accuracy over random selection for the same number of average information exchanges. Another key contribution of this paper is to use the cubature information filter as the local filter at the UAVs. In our simulation results, the cubature information filter showed a better tracking accuracy compared to the extended information filter.

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Appendix

The linear approximation of the innovation covariance $\mathbf{P}_{zz,i,j,k}$ at an UAV n_i and time k can be computed as

$$\mathbf{P}_{zz,i,j,k} = \mathbf{P}^T_{xz,i,j,k}\mathbf{Y}^T_{i,j,k|k-1}\mathbf{P}_{xz,i,j,k} + \mathbf{R}_{i,j,k}. \tag{19}$$

where $\mathbf{P}_{xz,i,j,k}$ and $\mathbf{R}_{i,j,k}$ are the cross covariance and measurement noise covariance of the object o_j at the UAV n_i and time k, respectively.