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UAV Team Decision and Control using Efficient Collaborative Estimation

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***Abstract*— A novel decision-estimation architecture for a team of agents cooperating under communication imperfections is presented. The scenario of interest is that of a group of uninhabited aerial vehicles performing cooperative task assignment under communication delays. In the proposed architecture, each UAV in the group runs multiple filters in parallel on: its own states, teammates' states, and its states as viewed by teammates. The estimation of team members' states allows each UAV to synchronize the transmitted cost of performing known tasks, obtained from the different group members, to a common time base. It also enables estimating the expected cost for teammates to prosecute new tasks. Thus, the group performance, under communication imperfections, can be improved. For the estimation, two different algorithms are proposed. The first is communication efficient in which asynchronous information updates are sent to the network by individual members based on the value of the information to the rest of the group. Taking into account that the plan and plant of each UAV are known to the rest of the group, improves the overall estimation process. Moreover, it allows proposing another, computationally efficient, estimation algorithm utilizing synchronous information updates.**

I. INTRODUCTION

Uninhabited aerial vehicles (UAVs) can be used for various civilian and military tasks. On top of the possibility of performing tasks without putting human life in harm's way, the lack of a human pilot allows significant weight savings and enables carrying out missions with unique characteristics, such as extremely long duration. Other important aspects are allowing new operational paradigms and being a force multiplier with minimal or no human intervention.

To realize these advantages, the UAVs must have a high level of autonomy and preferably work in groups. Exchanging information within the group is expected to synergetically improve the group's capability. In recent years numerous algorithms for performing collaborative specific tasks such as cooperative search [1] and classification [2] have been proposed. For solving cooperative multiple task assignment problems, involving for example classification, attack, and kill verification on multiple targets, emerging algorithms of different classes have been proposed, including: mixed integer linear programming [3], [4], iterative capacitated transhipment problem (CTP) algorithm [5], iterative auction [6], [7] and genetic algorithms [8].

Assuming perfect information flow, the above mentioned algorithms can be implemented in a redundant centralized manner in which each vehicle computes the cost for all vehicle-task combinations. However, in a realistic scenario communication constraints are expected. Information flow imperfections, such as communication delays, may produce different information sets for the different UAVs in the group leading to multiple strategies. The result can be uncoordinated assignments, such as multiple vehicles wrongly assigned to perform the same task on a certain target, leaving other tasks unassigned [9].

Decentralized implementation of the decision algorithms, such as iterative CTP and iterative auction, may reduce the sensitivity to communication imperfections [9]. In such an approach, each vehicle computes only its own cost to prosecute available tasks; and communicates this information to the rest of the group. A problem arises of synchronizing these costs to a common time base. In this paper we propose solving this problem by letting the UAVs also communicate information regarding their state. Thus, each UAV can employ an estimation algorithm on all of the team members' states enabling a time update of the individual received costs.

For the estimation process data need be fused from several sources. Data fusion topologies can be classified into three types: central, decentralized, and hierarchical. In the central topology one agent performs the data fusion of the information obtained from the different sensors. Thus, all measurements must be communicated to the central unit, involving high computational burden on that unit. In contrast, the decentralized topology is based on local fusion in each agent, of information communicated in the network. The decentralized topologies rely on communication between nearby agents. Thus, the communication messages are independent of the entire group size. This attribute allows scalability of the decentralized system to large group sizes. The hierarchical topology is a hybrid of the two former ones. In this paper decentralized collaborative estimation algorithms, featuring highly reduced communication and computational load, are presented.

The remainder of this manuscript is organized as follows: In the next section the UAV cooperative decision problem under information flow imperfections is posed. It is followed by the synthesis of computation and communication efficient decentralized estimation algorithms. A simulation

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study showing the performance of the new estimation algorithms is then presented. Concluding remarks are offered in the last section.

II. UAV Cooperative Decision Problem

The cooperative UAV task assignment problem in scenarios such as wide area search and destroy (WASD) [5] and combat intelligence surveillance and reconnaissance (ISR) serves as the background for the decision problem addressed in this paper. We first describe the centralized cooperative decision problem and then present a decentralized version of it. The effects of communication imperfections and the proposed modifications using decentralized estimation algorithms are then discussed.

A. Task Assignment Problem

Let $T = \{1, 2, ..., N_t\}$ be the set of targets found and let $V = \{1, 2, ..., N_v\}$ be a set of UAVs performing tasks on these targets. The goal of the task assignment algorithm is to make efficient use of the resources $v \subseteq V$, while prosecuting all the tasks on all the targets. For example, tasks associated with the WASD mission are search, classify, attack, and verify. Since the default task for unassigned vehicles is searching, it is not included in the assignment problem. Note that the multiple tasks per target (classify, attack, and verify) must be performed in order, *e.g.* a target must be classified before it can be attacked. There are many different cost functions that can be minimized in the task assignment problem such as total distance travelled by vehicles, or the time required to prosecute all of the targets. In this study the total accumulated cost for all of the vehicles to perform all of the tasks on all of the targets is used as the cost function. This assignment problem is posed as a combinatorial optimization problem in [8].

B. Decentralized Task Assignment Problem

As discussed earlier many different solutions to the task assignment problem have been proposed [3]–[8]. Being single assignment algorithms, running multiple times for the multiple tasks, the iterative CTP and auction algorithms are the natural candidates for decentralized implementation; promising reduced sensitivity to communication imperfections. In each iteration every vehicle computes the cost of performing the available tasks, based on its own information. This cost is denoted $c_{i,k}$ where $i \in V$ and $k \in T$. When one iteration is completed, any tasks left over, including follow-on tasks, are moved to the next iteration.

In the process of calculating costs, the vehicles rely on internal and external information. Thus,

$$c_{i,k} = f_i(\boldsymbol{x}_i, \boldsymbol{x}_e) \tag{1}$$

where $\boldsymbol{x}_i$ represents the vehicle's internal states and $\boldsymbol{x}_e$ represents the external ones. The internal states are defined as those that only the vehicle has access to (*i.e.* information that is not explicitly communicated to others) such as fuel levels, weapons status, etc. To the external states, such as the vehicle's position and it's targets, the other vehicles have access to. Note that the function f_i is known to all team members.

	Time	T_1	T_2	T_3
V_1	23.1	15660	55002	8654
V_2	21.6	17540	60324	23000
V_3	23.5	11344	74274	44306

Fig. 1: Cost matrix example.

When, for example, the iterative CTP is decentrally solved, costs from all of the vehicles are formed into a matrix. Each row corresponds to the cost, transmitted from one of the vehicles, to perform all the available tasks. In Fig. 1 such a matrix is presented for a scenario between 3 UAVs and 3 targets. Note that each row includes also a time stamp, indicating the time of when the computation of Eq. 1 has been performed by the representative vehicle.

C. Dealing with Communication Delays

In this study we assume a stationary known environment (fixed known targets) and that the communication imperfections cause uncertainty on teammates position and their respective updated costs. We utilize the important difference between internal and external states such that the external ones can be estimated by the other vehicles while the internal ones may not. We also assume that the internal states do not change in the time frame of importance. Thus, we concentrate here on estimating the position of teammates. Having estimates about the current location of teammates will enable synchronizing individual costs (rows in the decision matrix) from the different members to a common time basis, thus robustifying the group decision process with respect to communication delays. Moreover, it will allow each member to estimate the costs of the other vehicles to new targets based on prior communicated costs and information on their external states. This makes it possible to produce preliminary assignments prior to communicating with the other vehicles. The resulting preliminary assignment can be used to direct individual vehicles to expected trajectories, until all the costs for teammates to prosecute the new targets have been received and the assignment algorithm has been re-run.

III. Cooperative Estimation

In this section, first the general concept of decentralized estimation is discussed and then two such algorithms are derived for the investigated problem. One of the algorithms is computationally efficient while the other is communication efficient. Both algorithms utilize the information form of the Kalman filter.

A. Decentralized Estimation - Brief Review

Decentralized estimation is at the heart of many multi-sensor systems. It is composed of multiple agents having local information, that is shared through a communication network with neighboring agents; and then fused by different agents with their own local information. Algorithms for the optimal fusion of received information with local information in such a distributed network have been presented in [10]. In such algorithms local sensor data is processed to generate a local estimate that is then transmitted to other agents. The basic philosophy is that each agent reconstructs the optimal estimate as if all sensor measurements were transmitted instead of local estimates. The key step is in identifying the new information in the communicated local estimates in order to avoid double counting.

A well-known technique in data fusion algorithms is the information filter (IF) [11]. It is algebraically equivalent to the Kalman filter (KF) with a computationally simpler update stage at the cost of increased complexity in the time update stage. In this subsection the IF is summarized.

Consider the following linear system model:

$$\boldsymbol{x}_{k+1} = \boldsymbol{\Phi}_k \boldsymbol{x}_k + \boldsymbol{B}_k u_k + \boldsymbol{\Gamma}_k \omega_k, \qquad \boldsymbol{x}_k \in \mathbb{R}^n \tag{2}$$

where $\{u_k\}, u \in \mathbb{R}^l$ is the input vector and $\{\omega_k\}, \omega \in \mathbb{R}^p$ is a zero mean white sequence with positive semi-definite covariance matrix $\boldsymbol{Q}_k$ (process noise). The sensor observation is

$$\boldsymbol{z}_k = \boldsymbol{H}_k \boldsymbol{x}_k + \boldsymbol{v}_k, \qquad \boldsymbol{z}_k \in \mathbb{R}^m \tag{3}$$

where $\{v_k\}, v \in \mathbb{R}^m$ is a zero mean white sequence with positive definite covariance matrix R_k (measurement noise). $\{\omega_k\}$, $\{v_k\}$, and $\boldsymbol{x}_0$ are assumed to be mutually independent for all times.

The KF algorithm generates estimates for the state, denoted as $\hat{\boldsymbol{x}}$, together with a corresponding estimation covariance, denoted as $\boldsymbol{P}$. The IF, being a representation of the KF from the information viewpoint, uses the following definitions:

$$\boldsymbol{Y}_{(\cdot)/(\cdot)} \triangleq \boldsymbol{P}^{-1}_{(\cdot)/(\cdot)} \tag{4}$$

$$\hat{\boldsymbol{y}}_{(\cdot)/(\cdot)} \triangleq \boldsymbol{Y}_{(\cdot)/(\cdot)} \hat{\boldsymbol{x}}_{(\cdot)/(\cdot)} \tag{5}$$

$$\boldsymbol{I}_k \triangleq \boldsymbol{H}_k^T \boldsymbol{R}_k^{-1} \boldsymbol{H}_k \tag{6}$$

$$\boldsymbol{i}_k \triangleq \boldsymbol{H}_k^T \boldsymbol{R}_k^{-1} \boldsymbol{z}_k \tag{7}$$

where $\boldsymbol{Y}$ is the well-known Fisher information matrix, $\hat{\boldsymbol{y}}$ is the new estimated state vector, I is the *a priori* expected information held in each measurement, and i is the *a posteriori* actual information held in a single measurement. With these definitions, the IF can be summarized:

Time Update:

$$\hat{\boldsymbol{y}}_{k+1/k} = \left[\boldsymbol{1} - \boldsymbol{\Omega}_k \boldsymbol{\Gamma}_k^T\right] \boldsymbol{\Phi}_k^{-T} \left[\hat{\boldsymbol{y}}_{k/k} + \boldsymbol{Y}_{k/k} \boldsymbol{\Phi}_k^{-1} \boldsymbol{B}_k u_k\right] \tag{8}$$

$$\boldsymbol{Y}_{k+1/k} = \boldsymbol{M}_k - \boldsymbol{\Omega}_k \boldsymbol{\Gamma}_k^T \boldsymbol{M}_k \tag{9}$$

where

$$\boldsymbol{M}_k = \boldsymbol{\Phi}_k^{-T} \boldsymbol{Y}_{k/k} \boldsymbol{\Phi}_k^{-1} \tag{10}$$

$$\boldsymbol{\Omega}_k = \boldsymbol{M}_k \boldsymbol{\Gamma}_k \left[\boldsymbol{\Gamma}_k^T \boldsymbol{M}_k \boldsymbol{\Gamma}_k + \boldsymbol{Q}_k^{-1}\right]^{-1} \tag{11}$$

and $\boldsymbol{1}$ is the identity matrix with appropriate dimension and $\boldsymbol{Q}_k > 0$. If $\boldsymbol{Q}_k = 0$ then Eq. 9 is not applicable and $Y_{k+1/k} = M_k$.

Observation Update:

$$\hat{y}_{k+1/k+1} = \hat{y}_{k+1/k} + \boldsymbol{i}_{k+1} \tag{12}$$

$$\boldsymbol{Y}_{k+1/k+1} = \boldsymbol{Y}_{k+1/k} + \boldsymbol{I}_{k+1} \tag{13}$$

Note the additive nature of the observation update equations, making the IF a natural candidate for decentralized estimation.

B. Estimation Model

For obtaining a realtime solution of the cooperative task assignment problem it is usually assumed that the UAVs fly at a constant altitude and speed. For our derivation of a cooperative estimation algorithm we will make similar assumptions. Thus we use the Dubins car model [12] for representing the planar dynamics of the vehicles

$$\dot{x} = v \cos\theta \tag{14a}$$

$$\dot{y} = v \sin\theta \tag{14b}$$

$$\dot{\theta} = \Omega_{max} u \tag{14c}$$

$$\dot{v} = 0 \tag{14d}$$

where x and y are the UAV horizontal coordinates in a Cartesian inertial reference frame; θ is the azimuth flight angle; v is the speed; and Ω_{max} is the maximum turning rate of the vehicle (travelling at the speed of v). It was shown [12] that the optimal trajectories of vehicles having the dynamics of Eqs. 14 consist of straight lines and arcs with radius $R_{min} = v/\Omega_{max}$. More specifically, these optimal trajectories are from two different families: 1) turn-straight-turn, 2) turn-turn-turn. Let us assume that all vehicles abide to these strategies. Thus

$$u \in \{-1, 0, 1\} \tag{15}$$

We assume that each UAV has measurements only on its own position. Thus the measurement equation is

$$\boldsymbol{z}_k = \begin{bmatrix} x \\ y \end{bmatrix} + \boldsymbol{v}_k \tag{16}$$

and $\{\boldsymbol{v}_k\}, \boldsymbol{v} \in \mathbb{R}^2$ is a zero mean white sequence with positive definite covariance matrix R_k. we denote the measurement rate as f_1.

The equations of motion for the UAVs, given in Eqs. 14, are clearly nonlinear. For the estimation process we will be using the following state vector

$$\boldsymbol{x} \triangleq \begin{bmatrix} x & y & v_x & v_y \end{bmatrix}^T \tag{17}$$

with the dynamics

$$\dot{\boldsymbol{x}} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}(\boldsymbol{x})u + \boldsymbol{G}\omega \tag{18}$$

where

$$\boldsymbol{A}=\begin{bmatrix}0&0&1&0\\0&0&0&1\\0&0&0&0\\0&0&0&0\end{bmatrix};\boldsymbol{B}(\boldsymbol{x})=\begin{bmatrix}0\\0\\-\Omega_{max}v_y\\\Omega_{max}v_x\end{bmatrix};\boldsymbol{G}=\begin{bmatrix}0&0\\0&0\\1&0\\0&1\end{bmatrix} \tag{19}$$

We assume that each UAV knows the control actions of his teammates, since they are all acting based on the same cooperative team task assignment plan. Note that in the above representation of the equations of motion the dynamics matrix $\boldsymbol{A}$ is constant while $\boldsymbol{B}$ is state dependent. Thus, $\boldsymbol{A}$, and also $\boldsymbol{G}$, are identical to all vehicles, enabling the computationally efficient algorithm presented next.

C. Computationally Efficient IF

In this subsection we assume that each UAV receives synchronous updates from teammates at a constant rate $f_2 < f_1$. The transmitted/recieved data can be the raw measurements; better yet it can be the new information gained since the last transmission. Both will be discussed next.

We will denote the estimation of the state vector of UAV $j \in V$ by UAV $i \in V$ as $\hat{\boldsymbol{x}}^{i,j}$ and correspondly the IF state vector is denoted $\hat{\boldsymbol{y}}^{i,j}$. Note that $\hat{\boldsymbol{x}}^{i,i}$, represents the estimated state vector of UAV $i \in V$ by itself, based on the information transmitted to teammates. The estimation of ones own state, based on all available measurements, is denoted $\hat{\boldsymbol{x}}^{i}$. The distinction between $\hat{\boldsymbol{x}}^{i}$ and $\hat{\boldsymbol{x}}^{i,i}$ will become clear in the sequel.

The equations of the N_v IFs run by each UAV $i \in V$, based on the communicated information, at a rate of f_2, are:

Time Update:

$$\hat{\boldsymbol{y}}^{i,j}_{k+1/k}=\left[\mathbf{1}-\boldsymbol{\Omega}_k\boldsymbol{\Gamma}_k^T\right]\boldsymbol{\Phi}_k^{-T}[\hat{\boldsymbol{y}}^{i,j}_{k/k}\boldsymbol{Y}^{i,i}_{k/k}\boldsymbol{\Phi}_k^{-1} \boldsymbol{B}_k(\boldsymbol{Y}^{i,i}_{k/k}{}^{-1}\boldsymbol{y}^{i,j}_{k/k})u^j_k] \quad \forall \quad j\in V \tag{20}$$

$$\boldsymbol{Y}^{i,i}_{k+1/k}=\boldsymbol{M}_k-\boldsymbol{\Omega}_k\boldsymbol{\Gamma}_k^T\boldsymbol{M}_k \tag{21}$$

where $\boldsymbol{M}_k$ and $\boldsymbol{\Omega}_k$ are computed based on Eq. 10 and Eq. 11, respectively; $\boldsymbol{\Phi}_k$, $\boldsymbol{B}_k$ and $\boldsymbol{\Gamma}_k$ are the discrete versions of $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{G}$, respectively; and u^j_k is the control action of UAV $j \in V$ known to UAV $i \in V$ (the one performing the estimation process), since it is assumed that all the UAVs abide to the same task assignment plan.

Observation Update:

$$\hat{\boldsymbol{y}}^{i,j}_{k+1/k+1}=\hat{\boldsymbol{y}}^{i,j}_{k+1/k}+\boldsymbol{i}^j_{k+1} \quad \forall \quad j\in V \tag{22}$$

$$\boldsymbol{Y}^{i,i}_{k+1/k+1}=\boldsymbol{Y}^{i,i}_{k+1/k}+\boldsymbol{I}^j_{k+1} \tag{23}$$

Note that since the quality of information obtained from each UAV is assumed identical then Eqs. 21 and 23 can be computed only once for all filters; thus, reducing considerably the computational effort.

Each UAV also runs another IF on its own states using its measurements at a rate of $f_1 > f_2$. The equations for the state vector $\boldsymbol{y}^i$ and information matrix $\boldsymbol{Y}^i$ of such filter are identical to the ones given in Eqs. 8 - 13, except that $\boldsymbol{B}_k$ is state dependent, as in Eq. 20.

The transmitted information to the UAV group is $\boldsymbol{i}^j_k$ and $\boldsymbol{I}^j_k$. If this information is the current measurement then $\boldsymbol{I}^j_k$ and $\boldsymbol{i}^j_k$ can be computed based on Eqs. 6- 7, respectively. However, it will be more beneficial to send all the gathered information since the last transmission. Such information can be computed as

$$\boldsymbol{I}^j_k=\boldsymbol{Y}^j_{k/k}-\boldsymbol{Y}^{j,j}_{k/k} \tag{24}$$

$$\boldsymbol{i}^j_k=\boldsymbol{y}^j_{k/k}-\boldsymbol{y}^{j,j}_{k/k} \tag{25}$$

D. Communication Efficient IF

In this subsection we assume that each UAV receives asynchronous updates from teammates. The transmitted/recieved data $\boldsymbol{I}^j_k$ and $\boldsymbol{i}^j_k$ is based on the quality of the current state estimate of UAV $j \in V$ by UAV $i \in V$ as expected by UAV $j \in V$. Thus, the information is sent to the group members by UAV $j \in V$ only if

$$\boldsymbol{e}_j^T\boldsymbol{E}\boldsymbol{e}_j>\epsilon \tag{26}$$

where

$$\boldsymbol{e}_j=\boldsymbol{Y}^j_{k/k}{}^{-1}\boldsymbol{y}^j_{k/k}-\boldsymbol{Y}^{j,j}_{k/k}{}^{-1}\boldsymbol{y}^{j,j}_{k/k} \tag{27}$$

$$\boldsymbol{E}=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&0&0\\0&0&0&0\end{bmatrix} \tag{28}$$

and ϵ is a design parameter; and E was chosen so that the error will be defined between the position estimates.

The equations of the N_v IFs, run by each UAV $i \in V$ based on the communicated information, are:

Time Update:

$$\hat{\boldsymbol{y}}^{i,j}_{k+1/k}=\left[\mathbf{1}-\boldsymbol{\Omega}_k\boldsymbol{\Gamma}_k^T\right]\boldsymbol{\Phi}_k^{-T}[\hat{\boldsymbol{y}}^{i,j}_{k/k}+\boldsymbol{Y}^{i,j}_{k/k}\boldsymbol{\Phi}_k^{-1}\boldsymbol{B}_k (\boldsymbol{Y}^{i,j}_{k/k}{}^{-1}\boldsymbol{y}^{i,j}_{k/k})u^j_k] \quad \forall \quad j\in V \tag{29}$$

$$\boldsymbol{Y}^{i,j}_{k+1/k}=\boldsymbol{M}^{i,j}_k-\boldsymbol{\Omega}^{i,j}_k(\Gamma^{i,j}_k)^T\boldsymbol{M}^{i,j}_k \quad \forall \quad j\in V \tag{30}$$

where

$$\boldsymbol{\Omega}^{i,j}_k=\boldsymbol{M}^{i,j}_k\boldsymbol{\Gamma}_k\left[\boldsymbol{\Gamma}_k^T\boldsymbol{M}^{i,j}_k\boldsymbol{\Gamma}_k+\boldsymbol{Q}_k^{-1}\right]^{-1} \quad \forall \quad j\in V \tag{31}$$

$$\boldsymbol{M}^{i,j}_k=\boldsymbol{\Phi}_k^{-T}\boldsymbol{Y}^{i,j}_{k/k}\boldsymbol{\Phi}_k^{-1} \quad \forall \quad j\in V \tag{32}$$

Observation Update:

$$\hat{\boldsymbol{y}}^{i,j}_{k+1/k+1}=\hat{\boldsymbol{y}}^{i,j}_{k+1/k}+\boldsymbol{i}^j_{k+1} \quad \forall \quad j\in V \tag{33}$$

$$\boldsymbol{Y}^{i,j}_{k+1/k+1}=\boldsymbol{Y}^{i,j}_{k+1/k}+\boldsymbol{I}^j_{k+1} \quad \forall \quad j\in V \tag{34}$$

Note the significantly larger computational complexity of this algorithm compared to the one presented in the previous subsection. This complexity results from the need of calculating Eqs. 30, 34 N_v times compared to only once for the computation efficient algorithm (see Eqs. 21, 23).

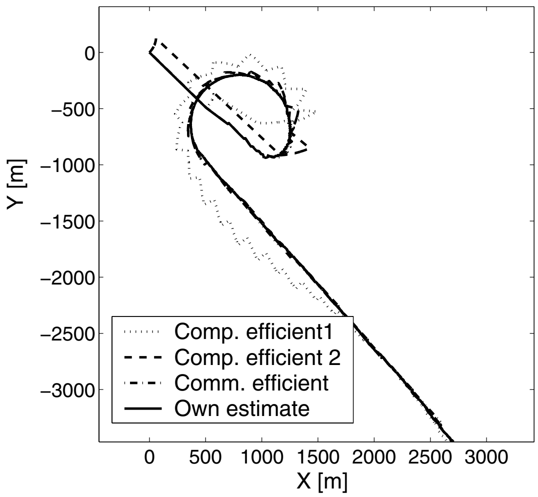

Fig. 2: Sample run estimation performance.

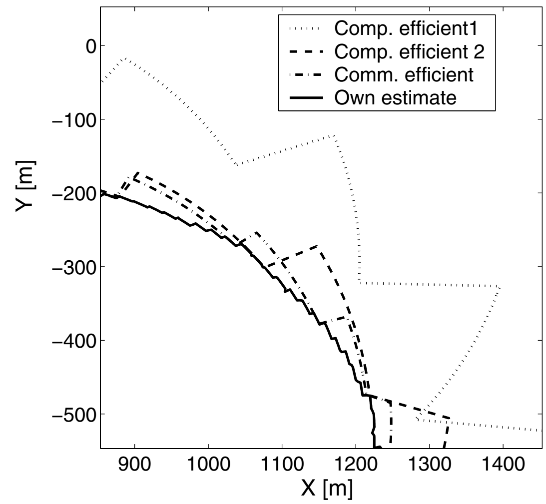

Fig. 3: Sample run estimation performance (zoom in).

IV. Algorithm Implementation

In this section the performance of the proposed estimation algorithm is examined. First, the performance of the computation and communication efficient estimation algorithms is studied using a simplified simulation. Then, the communication efficient algorithm is evaluated using the MultiUAV simulation [13].

A. Simplified Simulation

First, the performance of the developed decentralized estimation algorithms is evaluated using a simplified simulation of the vehicles' dynamics, based on Eqs. 14. The three examined algorithms are denoted: (i) comp. efficient 1 - raw measurements are transmitted, (ii) comp. efficient 2 - all new information gained from last communication is transmitted, (iii) comm. efficient - communication is sent based on the information measure of Eq. 26. Sample performance of the three different algorithms is presented in Figs. 2-3 where Fig. 3 presents a zoom in on a part of the trajectory. In this sample run, the UAV, of which the trajectory is estimated by one of its teammates, performs a counter clockwise maneuver followed by a non-maneuverable straight line flight. It is apparent that the best estimate is that of the UAV of itself while that of algorithm (i) performed by teammates based only on periodic measurements sent from that vehicle, at a low rate of f_2, is the worst. The best estimate by teammates is achieved by using algorithm (iii) which uses information sent based on its need. Note also from Fig. 3 the non-periodic nature of the communicated information when using algorithm (iii).

B. MultiUAV Simulation

The performance of the proposed communication efficient estimation algorithm was also evaluated using the MultUAV simulation testbed containing high fidelity vehicle dynamics, inter-vehicle communications, target sensors, targets, and threats. In the simulated scenario two UAVs perform multiple tasks on two targets. The UAVs communicate information with a known delay of 2sec. In Fig 4 the actual and estimated trajectories of the two cooperating UAVs are plotted where the filled rectangles represent the position of the two targets being flown over by the two UAVs.The asynchronous observation updates are evident. Note that in this example the total distance travelled by the UAVs to accomplish all the tasks was approximately 80Km. For comparison, the cost for the case of perfect information was approximately 57Km, while that for a pure delay implemented without the proposed estimation-decision scheme was approximately 100Km.

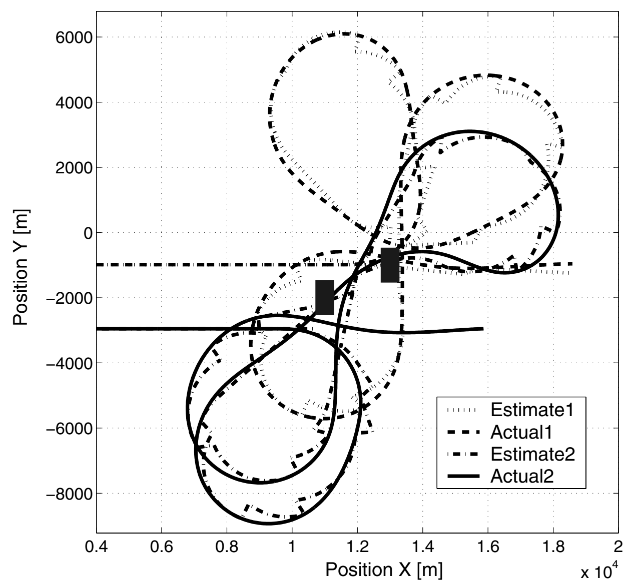

Fig. 4: Sample trajectories of cooperating UAVs.

V. Conclusions

A novel decision-estimation architecture for a team of unmanned aerial vehicles cooperating under communication imperfections has been presented. For the estimation process each UAV in the group runs multiple filters in parallel on: its own states, teammates' states, and its states as viewed by teammates. The estimation of team members' states allows synchronization of the costs obtained from individual UAVs to known targets; and also enables immediately estimating teammates' costs to performing tasks on newly found targets. Thus, a group's decentralized decision process, under communication imperfections, can be improved.

Taking into account that the plan and plant of each UAV team member is known to the rest of the group improves the overall estimation process. Moreover, it allowed to greatly reduce the computational complexity of the proposed algorithm rendering its implementation in realistic scenarios feasible. It was also shown that the amount of communication within the team can be tuned, based on the value of the information to the receiving end.

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