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Published in:
IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING

DOI:
10.1109/TASE.2021.3135834

E-pub ahead of print: 23/12/2021

Document Version
Publisher's PDF, also known as Version of record

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Please cite the original version:
Doostmohammadian, M., Taghieh, A., & Zarrabi, H. (2021). Distributed Estimation Approach for Tracking a Mobile Target via Formation of UAVs. IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, 1-12. [9662276]. https://doi.org/10.1109/TASE.2021.3135834
Distributed Estimation Approach for Tracking a Mobile Target via Formation of UAVs

Mohammadreza Doostmohammadian, Amin Taghieh, and Houman Zarrabi

Abstract—This paper considers distributed estimation methods to enable the formation of Unmanned-Aerial-Vehicles (UAVs) that track a moving target. The UAVs (or agents) are equipped with communication devices to receive a beacon signal from the target and share information with neighboring UAVs. The shared information includes the time-of-arrival (TOA) of the beacon signal from the target and estimates on the target's location. Every UAV processes the received information from the neighbors using a single-time-scale distributed estimation protocol. This differs from multi-time-scale protocols that require (i) many consensus iterations on a-priori estimates, (ii) fast communication among agents (in general, much faster than the sampling rate of the target dynamics), and thus, more-costly communication equipment and processing units. Further, our approach outperforms most single-time-scale methods in terms of observability assumption as these methods assume that the target is observable via the measurement data received from neighboring UAVs (referred to as local-observability). This requires more communications among the sensors. In contrast, our approach is only based on global-observability assumption, and thus, requires less networking (only strong-connectivity) and communication traffic along with less computational load by data-processing once at the same time-scale of sampling target dynamics. We consider modified time-difference-of-arrival (TDOA) measurements with a constant output matrix for the linearized model. UAVs make a pre-specified formation, and by estimating the target's location via these measurements, move along with the target.

Note to Practitioners—Inspired by recent development in industrial UAVs along with emerging progress in low-cost processing units, fog computing systems, and wireless communications, this paper considers mobile tracking of a moving target via a group of wireless-connected autonomous drones. In the classical tracking methods, which are prone to single-point-of-failure, all the sensors need to send their information to a ground central station over a long-range and costly data-transmission channel. In contrast, by collaborative tracking the processing and decision-making are distributed among a swarm of drones equipped with onboard miniaturized electronic parts such as sensors, microcontrollers, microprocessors, and communication units. This article provides an efficient algorithm to enable such drones to autonomously track the moving target in real-time. Note that the cost and tracking ability of the UAV swarm are directly determined by the computational efficiency and communication burden of the estimation algorithm. In this regard, most available estimation algorithms are over budget and even infeasible due to the need for fast data-transmission channels, fast CPUs, and high network traffic. Our proposed estimation technique outperforms similar algorithms in terms of required communication bandwidth, data-transmission rate, and computational resources, which considerably reduces the hardware cost and improves tracking efficiency in real-time large-scale applications. We show the feasibility and efficiency of our distributed tracking method by simulation.

Index Terms—Target tracking, distributed estimation, observability, structural analysis, multilateration, formation, consensus.

I. INTRODUCTION

TRACKING moving targets has been a topic of interest in signal processing and control literature [1]–[5]. The main objective of target tracking is to estimate the trajectories of a mobile target, with different civilian, military, and transportation applications. Different dynamic models are considered in the literature, refer to [2] for a comprehensive survey. Among the models, the Nearly-Constant-Velocity (NCV) dynamic model is considered in this paper. The target position is estimated based on some measurements. The typical measurements are based on time-of-arrival (TOA) [6], angle-of-arrival (AOA), received-signal-strength (RSS) [7], [8], image-processing-based [9], [10], or a combination of these. A survey of different measurement techniques is given in [3]. In this paper, the difference of TOA measurements or multilateration technique is adopted for tracking. The UAVs (also referred to as agents) typically share their location and TOA information, based on which they can estimate the location of the target. The network connectivity is a challenge in multi-UAV tracking, in contrast to single-UAV tracking [9]. The literature also includes the tracking of multiple targets by static sensors [11], [12] and mobile agents [13] using different filtering scenarios. Further, in contrast to ground nonholonomic robots equipped with overhead cameras in [10], [14], this paper considers aerial drones for tracking purposes based on TOA measurements of a beacon signal. Recent development of UAV technology and multi-drone coordination [15]–[18] motivates industrial application of such mobile tracking methods.

Manuscript received 19 November 2021; accepted 13 December 2021. Date of publication 23 December 2021; date of current version 13 October 2022. This article was recommended for publication by Associate Editor M. Franceschelli and Editor C. Seatzu upon evaluation of the reviewers’ comments. (Corresponding author: Mohammadreza Doostmohammadian.) Mohammadreza Doostmohammadian is with the Mechatronics Department, Faculty of Mechanical Engineering, Semnan University, Semnan 3513119111, Iran, and also with the School of Electrical Engineering, Aalto University, 02150 Espoo, Finland (e-mail: doost@semnan.ac.ir; mohammadreza.doostmohammadian@aalto.fi).
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Color versions of one or more figures in this article are available at https://doi.org/10.1109/TASE.2021.3135834.
Digital Object Identifier 10.1109/TASE.2021.3135834.

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Various estimation techniques for tracking are adopted in the literature, mostly centralized [19]–[24]. In other words, in these scenarios, all the measurement information is sent to and collected in a fusion center. This center performs different estimation techniques such as Kalman Filter (KF), Extended Kalman Filter (EKF), Maximum Likelihood Estimation (MLE), or a combination of these to estimate the state (position) of the target [21]–[23], [25]. Recent development in cloud-based techniques and distributed computing [26], [27] along with IoT technology [16]. [28] has motivated decentralized solutions for estimation [29]–[36]. These approaches are based on sharing and averaging the estimates locally, over a distributed network of agents, instead of long-range communication to the fusion center. This averaging or data fusion is mainly based on consensus protocols [37], [38]. One main concern in decentralized estimation is observability constraint. For UAVs to reach a converging estimate with stable steady-state error some observability conditions must be satisfied. The works [29]–[36] use a semi-centralized approach in which the system is observable in the neighborhood of every agent. In other words, every UAV needs to receive necessary information on the target state directly from its neighbors. This requires densely-connected communication network, where according to [36] (at least) 3 neighbors need to share their measurement information with every UAV. However, recently distributed estimation protocols are proposed in [39]–[49], in which no local observability in the neighborhood of any UAV is required. Among these, two different scenarios are proposed: (i) multi-time-scale (MTS) estimation [39]–[45],1 and (ii) single-time-scale (STS) estimation [46]–[49]. The former scenario requires many iteration of consensus and data-sharing in between every two consecutive time-step of the system dynamics, where the estimation performance tightly depends on the number of such iterations. Therefore, for performance-guarantee, this scenario requires much faster communication/computation rate than system dynamics, which might be very costly and even infeasible in large-scale applications. On the other hand, the STS scenario, proposed in [46]–[48] and further developed in [49], only one iteration of consensus and information sharing is required, which significantly reduces the communication/computation-related costs. In this paper, notion of distributed observability [55] is considered, which is a milder condition compared to local observability. This notion relates the structure of the multi-UAV network (or sensor network) to the target dynamics (or system structure in general), and establishes the observability of the distributed estimation network. This notion, further, simplifies the observability analysis of general composite systems.

This work develops a variant of our networked estimation protocol in [49] for target tracking purposes. In particular, the protocol in this paper, in contrast to [49], does not require output-fusion and is only based on data-fusion on a-priori estimates. This reduces the communication and computation burden on UAVs as compared to [49]. Adopting this networked estimation protocol, it can be proved that the communication network of UAVs for target tracking is sufficient to be strongly-connected (SC), as compared to the hub-based connectivity requirement for measurement-fusion in [49]. This is one of the main contributions of the paper, i.e. to give distributed tracking technique with the least connectivity requirement on the communication network of agents. Recall that this protocol benefits from all the merits of STS distributed estimation, including: (i) relaxing the local observability assumption as compared to [29]–[36], which, in turn, lessens the network connectivity to strong-connectivity; (ii) requiring less number of data-sharing/consensus iterations as compared to MTS estimation [39]–[45], which significantly reduces the computation/communication rate over the network. Furthermore, this protocol improves existing STS methods in terms of reducing the network connectivity requirement. The communication rate and network connectivity requirements are compared via simulation and theory.

In this work, we assume the UAVs follow the target in a pre-specified formation shape. It should be mentioned that the main contributions of this work are on using networked estimation and relaxing the multi-UAV network connectivity, while the formation scenario, by mixing the strategies in [37], [56], [57], is used for the purpose of following the target to keep it in the range of UAVs. Note that different formation strategies are proposed in the literature [18], [37], [56]–[64]. In this work, we adopt a variant of the distance-based formation scenario initially introduced in [56] and further developed in [37] by adding barycentric-coordinate-based method in [57]. As compared to the static formation scenarios in [37], [56], the formation scenario in this paper is more rigid (using the results in [57]) and, further, is dynamic as UAVs move along with the target in formation, i.e., the formation strategy is modified as a leader-follower protocol with the target object as the leader and the UAVs as the followers. This paper considers single-target tracking and not multi-target tracking as in [11], [12]. This is because the UAVs move and follow the target in formation, while in multi-target tracking the sensors are static in fixed positions. The proof of formation stability straightly follows from [37], [56], [57] and skipped due to space limitation.

In general, distributed algorithms prevent single-node-of-failure by localizing the computation and tracking. This enables designing q-redundant observers resilient to failure of (up-to) q sensors or losing q communication channels. In our tracking scenario, one can further design q-redundant distributed estimators by considering survivable-network-design [65], [66], i.e., to extend the distributed tracking method such that the UAVs can also detect (and isolate) possible fault or attack in the TOA measurements, for example, via stateful detection [52, Algorithm 1] or stateless detection [50], [51, Algorithm 1] (considering UAVs as Type-β agents). Isolating the faulty measurement and UAV, the rest of the UAVs can proceed with their estimation/tracking by reshaping the formation and networking (as far as their network is strongly-connected).

1In another perspective, [42], [43] further address joint distributed sensor attack detection along with estimation, where similarly our results can be easily extended to simultaneously detect possible sensing anomalies via the FDI methodology in [50] and attack detection/mitigation strategy in [51], [52]. Similar results are also discussed in [53], [54].
This is in contrast to the semi-centralized and many locally-observable STS strategies prone to faulty measurement data. To summarize, this paper advances the state-of-the-art in terms of reducing the linking and communication/processing rate via distributed tracking strategies and localizing data-processing to avoid single-node-of-failure.

The rest of the paper is organized as follows. Section II formulates the problem. Section III provides the proposed networked estimation approach, and its error stability analysis is discussed in Section IV. Section V explains the adopted formation strategy. Simulation is provided in Section VI for comparison. Finally, Section VII concludes the paper.

II. TARGET MODEL AND PROBLEM FORMULATION

A. Dynamic Model of the Mobile Target

Various dynamic models for a mobile target exist in the literature [2], [67], among which the Nearly-Constant-Velocity (NCV) model has recently been adopted for target tracking scenarios [2], [36], [67]. In this model, the following discrete-time state-space model governs the state-vector of the target:

\[
x(k + 1) = F_k x(k) + G_k w(k),
\]

where \( F_k \) and \( G_k \) respectively are known as the transition matrix and the input matrix at time-step \( k \), and \( w(k) \) as input which is considered to follow a random process (white noise).

The state vector \( x \) represents the Cartesian coordinates of the position \( p = (p_x; p_y; p_z) \) and velocity \( \dot{p} = (\dot{p}_x; \dot{p}_y; \dot{p}_z) \) of the mobile target as follows:

\[
x = \begin{pmatrix} p \\ \dot{p} \end{pmatrix} = \begin{pmatrix} p_x \\ p_y \\ p_z \\ \dot{p}_x \\ \dot{p}_y \\ \dot{p}_z \end{pmatrix}.
\]

For the NCV model, considering sampling time interval \( T \), the transition matrix and the input matrix are as follows:

\[
F_k = \begin{pmatrix} 1 & 0 & 0 & T & 0 & 0 \\ 0 & 1 & 0 & T & 0 & 0 \\ 0 & 0 & 1 & 0 & T & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix},
G_k = \begin{pmatrix} T^2 \\ T \\ 0 \\ 0 \\ 0 \\ T \end{pmatrix}.
\]

Note that we used the general time-dependent notations \( G_k, F_k \) throughout the paper in case the sampling period \( T \) changes in time. For a fixed sampling frequency, as in most literature, the matrices are time-independent and one can drop the dependence on \( k \) and use \( G, F \) (as in Section VI).

B. Multilateration-Based Measurements

The measurements from the target are based on the multilateration technique. This method, also known as pseudo-range-multilateration, is a navigation and surveillance technique that is based on the time-of-arrival (TOA) measurement of a beacon signal in the form of radio wave, acoustic wave, seismic wave, etc. This beacon signal has a known propagation speed \( c \). One can view multilateration as measuring \( n \) TOAs, and then, finding \( n - 1 \) TDOAs used for localization purposes. The group of UAVs share the TOAs of the beacon signal and their location information, calculate the TDOAs, and based on that localize the moving object. Consider every UAV\(^2\) to receive the beacon signal from the moving target. Knowing the propagation speed of the signal \( c \), the measurement at each UAV \( i \) (at time-instant \( k \)) is [6], [36], [68], [69],

\[
y_i(k) = h_i(x(k)) + r_i(k),
\]

where \( y_i \) is the measurement, and \( r_i \) is the white noise term at UAV \( i \) from a zero-mean Gaussian process. Let two UAVs \( i \) and \( j \) be neighbors if they can exchange information (over a communication network \( G_W \)). Each UAV \( i \) measures the (modified) TDOA of the signal received from the target and its neighbor \( j \in N_i \). Let \( t_i \) represent the time the beacon signal reached from the target to the UAV \( i \); then, the shared TOA is simply \( \|p(k) - p_i(k)\| = c t_i \) with \( p_i \) as the position of the \( i \)th UAV and \( p \) as the target position. Then, the measurement \( h_i \) (at UAV \( i \)) can be expressed as a function of \( p \) and, in turn, as a function of \( x \) in (2) [69]:

\[
h_i(x(k)) = \begin{pmatrix} h_{i,1}(x(k)) \\ h_{i,2}(x(k)) \\ \vdots \\ h_{i,|N_i|}(x(k)) \end{pmatrix},
\]

with \( |N_i| \) as the cardinality of the neighboring set \( N_i \). The modified TDOA measurement of two UAVs \( i \) and \( j \in N_i \) is defined as,

\[
h_{i,j}(x(k)) = \frac{1}{2}(\|p(k) - p_i(k)\|^2 - \|p(k) - p_j(k)\|^2),
\]

with \( \| . \| \) as the Euclidean norm. Eq. (6) can be simplified as,

\[
h_{i,j}(x(k)) = \frac{1}{2}((p_j^x - p_i^x)(2p_x^x - p_j^x - p_i^x) + (p_j^y - p_i^y)(2p_y^y - p_j^y - p_i^y) + (p_j^z - p_i^z)(2p_z^z - p_j^z - p_i^z)),
\]

with linearity on \( p = (p_x^c; p_y^c; p_z^c) \). In general, the linearized model from (6) is [69],

\[
y_i(k) = H_i x(k) + r_i(k),
\]

with the \( |N_i| \times 6 \) matrix \( H_i \) defined as,

\[
H_i = \begin{pmatrix} \frac{\partial h_{i,1}}{\partial p_x^c} & \frac{\partial h_{i,1}}{\partial p_y^c} & \frac{\partial h_{i,1}}{\partial p_z^c} & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial h_{i,j,|N_i|}}{\partial p_x^c} & \frac{\partial h_{i,j,|N_i|}}{\partial p_y^c} & \frac{\partial h_{i,j,|N_i|}}{\partial p_z^c} & 0 & 0 & 0 \end{pmatrix}.
\]

with \( N_i = \{j_1, \ldots, j_{|N_i|}\} \) as the set of neighbors of UAV \( i \). We drop the \( x \) and \( k \) dependence only for notation simplicity. For the modified TDOA measurement (6), we get,

\[
\begin{bmatrix}
\frac{\partial h_{i,j}}{\partial p_x^c} = p_{j,x}^c - p_{i,x}^c = p_{x,i}^c, \\
\frac{\partial h_{i,j}}{\partial p_y^c} = p_{j,y}^c - p_{i,y}^c = p_{y,i}^c, \\
\frac{\partial h_{i,j}}{\partial p_z^c} = p_{j,z}^c - p_{i,z}^c = p_{z,i}^c
\end{bmatrix} = H_i = \begin{pmatrix} p_{j,x}^c & 0 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ p_{j,|N_i|}^c & 0 & \ldots & 0 \end{pmatrix}.
\]

\(^2\)In this paper, we use UAVs throughout the paper for notation consistency. In the literature, similar terms as mobile agents or sensors are also used interchangeably.
with \( \mathbf{p}_{ij} = \mathbf{p}_j - \mathbf{p}_i \), denoting the relative position of neighboring UAVs \( i \) and \( j \), and \( \mathbf{p}_0 \) as the column vector of 0s of size 3. Then, the measurement matrix at every UAV \( i \) has \( |\mathcal{N}_i| \) rows each associated with neighboring UAV \( j \in \mathcal{N}_i \) as \( (p^j_1, p^j_2, p^j_3, 0, 0, 0) \) which is constant for fixed \( \mathbf{p}_{ij} \). This setup is illustrated in Fig. 1. Other similar TDOA-based works consider an alternative nonlinear measurement model to (6) as,

\[
h_{ij}(\mathbf{x}(k)) = \|\mathbf{p}(k) - \mathbf{p}_i(k)\| - \|\mathbf{p}(k) - \mathbf{p}_j(k)\|,
\]

and linearize the above for tracking purposes. See [6], [36], [68] for more details. Note that measurement model (6) is an improvement over the above nonlinear model (11), as its linearization (9)-(10) gives a constant output matrix that helps the gain design discussed later in Section IV.

C. Recall on Algebraic Graph Theory

The network (of agents/UAVs) is defined as \( \mathcal{G}_W = (\mathcal{V}, \mathcal{E}) \) with \( \mathcal{V} = \{1, \ldots, n\} \) as the set of nodes (agents) and \( \mathcal{E} = \{(i, j) | i \rightarrow j, i, j \in \mathcal{V}\} \) as the set of links (communications), where \( i \rightarrow j \) implies the link from node \( i \) to \( j \). The set of neighbors of node \( i \) is defined as \( \mathcal{N}_i = \{j | (j, i) \in \mathcal{E}\} \). Network \( \mathcal{G}_W \) is strongly-connected (SC) if for all \( i, j \in \mathcal{V} \), there is a path from \( i \) to \( j \). For a non-SC network \( \mathcal{G}_W \), define a SCC (strongly-connected-component) as a sub-network of \( \mathcal{G}_W \) in which every two nodes are connected via a path. Denote the associated weight matrix of the network \( \mathcal{G}_W \) by \( n \times n \) matrix \( W = [W_{ij}] \) with \( W_{ij} > 0 \) if \( j \in \mathcal{N}_i \) and \( W_{ij} = 0 \) otherwise. Further, \( W \) is called row-stochastic if \( \sum_{j=1}^{n} W_{ij} = 1 \).

D. Problem Statement

In this paper, the target dynamics follows Eq. (2)-(3), and a formation of UAVs equipped with sensing and communication accessories is considered to track this mobile target. Following a setup, e.g., as in Radar beacon (or racon), each UAV receives the beacon signal from the mobile target, along with some information from its neighbors. The group of UAVs, while making a formation, follow the target (to improve the TDOA-based measurements by getting closer to the target) and use the received information and TDOA measurements (8)-(9) to keep tracking the moving target. The challenge is to develop a networked estimation protocol with low computation/communication load on UAVs with stable steady-state tracking error. Further, the minimal requirement on the communication network of UAVs needs to be defined to satisfy distributed observability. The link density of the network is tightly related to the observability requirements of the estimation technique. The prevalent approach in the literature assumes the network is observable in the neighborhood of each UAV. This condition is known as local observability and is adopted in many estimation scenarios (discussed in Section I). To reduce the number of communication links, an advanced networked estimation technique based on global observability is needed with the least connectivity requirement on the communication network of UAVs, as proposed in the coming sections.

III. Tracking Based on Distributed Estimation

Distributed estimation protocols are widely used in multi-agent systems and sensor networks. As mentioned before and shown in Fig. 2, MTS networked estimation protocols [39]–[45] mandate high communication and processing load at UAVs. Therefore, these methods are not desirable (or even cost-feasible) for target tracking purposes. This section proposes a STS networked estimation protocol where the time-scales of communication and system dynamics are the same, see Fig. 2. This is more preferred in real-time applications, e.g., for the target-tracking scenario in this paper.

The proposed networked estimation technique is a variant of the protocol in [49] with some modifications in terms of network connectivity requirement and shared information. In [49], the networked estimation requires sharing both a-priori estimates and state measurements, while this work only relies on sharing a-priori estimates. In terms of network connectivity, [49] requires certain agents to communicate as hubs (i.e., share their information with all other agents), while in this work no such network connectivity is needed. Every UAV \( i \) receives the estimates \( \mathbf{x}_i(k - 1) \) from its neighboring UAVs \( j \in \mathcal{N}_i \) and calculates the a-priori estimates as follows,

\[
\mathbf{x}_i(k) = \sum_{j \in \mathcal{N}_i} W_{ij} \mathbf{f}_{k-1} \mathbf{x}_j(k - 1),
\]

where \( n \times n \) fusion matrix \( W \) is associated with the UAVs’ network and is subject to the following two conditions:

1) \( W \) is row-stochastic.
2) All diagonal entries of \( W \) are non-zero, i.e., \( W_{ii} \neq 0 \) for \( i = 1, \ldots, n \). The former is necessary for consensus on estimates and the latter implies that each UAV uses its own information to update its a-priori estimate. Next, using multilateration measurements, every UAV updates its estimate of the target state as follows,

\[
\tilde{x}_i(k) = x_i(k) + K_{i,k} H_i^T (y_i(k) - H_i \tilde{x}_i(k)),
\]

where \( K_{i,k} \) is the matrix of estimation (or observer) gain of UAV \( i \) at step \( k \). Notice that Eq. (13) is involved with no measurement sharing. In a centralized setup, one can design reduced-order observers using the measurable states \( p \) given the \( H_i \)s at a fusion center [20], which differs from our distributed setup.

Remark 1: Using consensus fusion on a-priori estimates in (12) can significantly reduce the number of needed communications over the network. In case of no consensus fusion (only using measurement-update or innovation) with the minimum number of sensors, an all-to-all communication network is needed to make the system observable to all other sensors [29], i.e., a network of \( N(N-1) \) linking. Using fusion algorithms, e.g., for the target dynamics (1)-(3), 4 measurements (3 other sensor measurements + the measurement of sensor itself) is sufficient for localization over a distributed sensor network [70]–[72], i.e., a network of \( 3N \) linking.

Next, define the estimation error of UAV \( i \) as \( e_i(k) = x(k) - \tilde{x}_i(k) \). For the estimator (12)-(13) the error dynamic of the \( i \)th UAV can be derived as follows,

\[
e_i(k) = x(k) - \sum_{j \in N_i} W_{ij} F_{k-1} \tilde{x}_j(k-1) + K_{i,k} H_i^T (y_i(k) - H_i \sum_{j \in N_i} W_{ij} F_{k-1} \tilde{x}_j(k-1)).
\]

By substituting (1) and (8) in above and some algebraic manipulation, we get,

\[
e_i(k) = F_{k-1} x(k-1) + G_{k-1} w(k-1) - \sum_{j \in N_i} W_{ij} F_{k-1} \tilde{x}_j(k-1)
- K_{i,k} \left( H_i^T H_i (F_{k-1} x(k-1) + G_{k-1} w(k-1)) + H_i^T r_i(k) - H_i \sum_{j \in N_i} W_{ij} F_{k-1} \tilde{x}_j(k-1) \right).
\]

Recall that the row-stochastic condition of \( W \) implies that \( \sum_{j=1}^n W_{ij} = 1 \). Since \( W_{ij} = 0 \) for \( j \notin N_i \), we have,

\[
F_{k-1} x(k-1) = \sum_{j \in N_i} W_{ij} F_{k-1} x(k-1),
\]

and consequently substituting the above in (15) we get,

\[
e_i(k) = \sum_{j \in N_i} W_{ij} F_{k-1} e_j(k-1)
- K_{i,k} H_i^T H_i \sum_{j \in N_i} W_{ij} F_{k-1} e_j(k-1) + \eta_i(k),
\]

where \( \eta_i \) collects the noise terms and random inputs. Now define the global error and collective noise at all UAVs as,

\[
e(k) = (e_1(k); \ldots; e_n(k)), \quad \eta(k) = (\eta_1(k); \ldots; \eta_n(k)).
\]

Then, the global error dynamics follows as,

\[
e(k) = (W \otimes F_{k-1} - K_k D_H (W \otimes F_{k-1})) e(k-1) + \eta(k),
\]

with the block-diagonal matrices \( D_H \triangleq \text{blockdiag}(H_1^T H_1) \) and \( K_k \triangleq \text{blockdiag}(K_i) \). The term \( \eta \) is as follows,

\[
\eta(k) = \mathbf{1}_n \otimes G_{k-1} w(k-1) - K_k (D_H (\mathbf{1}_n \otimes G_{k-1} w(k-1)) + \overline{D}_H r(k)),
\]

where \( r = (r_1; \ldots; r_n) \), \( \mathbf{1}_n \) is the size \( n \) (column) vector of all ones, and block-diagonal matrix \( \overline{D}_H \triangleq \text{blockdiag}(H_i) \).

We assume fixed non-switching networks and thus \( W \) is independent of \( k \). In the next section, we derive the conditions for error stability of (17).

IV. ERROR STABILITY ANALYSIS VIA STRUCTURED SYSTEM THEORY

In this section, the stability of error dynamic (17) is analyzed. The error dynamic (17) is stable if there exist a feedback gain matrix \( K_k \) such that (for all \( k \)),

\[
\rho (W \otimes F_{k-1} - K_k D_H (W \otimes F_{k-1})) < 1
\]

where \( \rho \) is the spectral radius. Following the Kalman stability theorem and observer error stability analysis in [73], there exist gain matrices \( K_k \) to satisfy (19) if the pair \( (W \otimes F_{k-1}, D_H) \) is observable. This is known as the distributed observability [55] and implies (networked) observability at every UAV in a distributed way. To satisfy distributed observability the structure of matrix \( W \) needs to meet certain conditions.

Recall that observability (and controllability) are structural (or generic) properties [55], [74]–[78]. Therefore, in this paper, we adopt such an approach to determine the structure of \( W \) based on the structure of the system. In other words, we structurally design the zero-nonzero pattern of \( W \) (or the associated multi-agent graph \( \mathcal{G}_w \) based on the structure of \( D_H \) and \( F_{k-1} \) such that \( (W \otimes F_{k-1}, D_H) \) is structurally observable. Such observability holds for almost all random choices for entries of \( W \). The structural observability of the pair \( (W \otimes F_{k-1}, D_H) \) tightly depends on the structural rank (or S-rank)\(^3\) of the matrix \( F_{k-1} \). The system matrix \( F_{k-1} \) is full S-rank (S-rank(\( F_{k-1} \)) = \( n \)) as all its diagonal entries are fixed non-zero (or free entries).\(^4\) For a similar reason, the \( W \) matrix is also full S-rank. Structural observability is, in general, examined on the graph representation of the system matrix, also known as the system digraph.\(^5\) The necessary structural conditions for observability (and the dual problem of controllability) of system digraphs are derived in [82].

\(^3\)For a matrix, the S-rank is defined as the number of free entries (the entries which are not fixed-zero) in its distinct rows and columns, i.e., the number of non-zero entries of the matrix that share no rows and columns determines the S-rank. Observability of S-rank-deficient matrices (and estimation of rank-deficient systems), in general, needs more outputs as discussed in [79].

\(^4\)Recall that a system with fixed non-zero diagonal entries in its associated adjacency matrix is called self-damped [80], [81]. Similarly, a network is called self-damped if every node has a self-cycle.

\(^5\)Define the system digraph as a network/graph in which every state represents a node and the fixed non-zero entries of the system matrix represent the links [82]. Such a digraph represents the system structure.
In [82], it is shown that for a full S-rank system, outputs of parent nodes (or in general parent SCCs) are necessary and sufficient for structural observability. The concept of parent node/SCC is defined as the node/SCC with no outgoing links to other nodes/SCCs in the system digraph. Recalling the matrix $F_{k-1}$ and measurements given by equations (8)-(10), one can see that observability conditions for $F_{k-1}$ are satisfied by measuring position states $p^x, p^y, p^z$ as the parent state nodes. The next step is to design the structure of $W$ matrix to gain distributed observability (in the generic sense).

Theorem 1: Having the measurements (8)-(10) from target state, $(W \otimes F_{k-1}, D_H)$-observability is satisfied if $W$ is irreducible.\(^6\)

Proof: The proof of the above theorem follows from [82]. Consider the digraphs $G_W$ and $G_F$ associated with the given $W$ and $F$ matrices. It is known that the following two conditions ensure structural observability of a digraph: (i) the output-connectivity, and (ii) the S-rank condition. Having the $F_{k-1}$ and $W$ matrices to be full S-rank, the S-rank condition is already satisfied. Having $D_H$ to contain the measurements of parent nodes/SCCs, the output-connectivity condition (for structural observability of $(W \otimes F_{k-1}, D_H)$) follows from the output connectivity (and structural observability) of the Kronecker product network of $G_W$ and $G_F$. From [82, Theorem 4], this is satisfied if the network $G_W$ is SC, i.e., its associated matrix $W$ is irreducible. This completes the proof.

Theorem 1 implies that for the group of UAVs to track the state of the target with bounded estimation error, the communication network of UAVs needs to be SC. It should be mentioned that in target tracking scenarios the communication links among UAVs are typically bidirectional, i.e., the network is undirected. In this case, a connected network of UAVs satisfies the irreducibility conditions in Theorem 1. For a fixed sampling period $T$ and an irreducible matrix $W$ (with row-stochastic entries), one can design feedback gain $K$ such that the error is steady-state stable. In the rest of the paper, we assume constant $T$ (fixed sampling rate), and thus, the matrices $F, G$ and consequently $K$ are independent of time-step $k$. The time-dependent notation in (19) is given in its most general form. Note that $K$ needs to be block-diagonal such that each UAV only gets feedback of its own local information and admits the SC network design. To design such gain matrices, Linear-Matrix-Inequalities (LMI) approach can be adopted. Interested readers are referred to [49], [83] for details on such a $K$ design. The LMI $K$ design, further, can be subject to a constraint on the spectral radius in (19) to be bounded by $\tilde{\sigma} < 1$. This ensures a certain convergence rate of the closed-loop dynamics; however, this may increase the running time of solving the LMI since the set of possible solutions is reduced by bound $\tilde{\sigma}$. In general, there is a trade-off between using smaller $\tilde{\sigma}$ and the running time of LMI design. See more on convergence rate in [84]. An approximation of error variance at every UAV can be derived via the results in [50], [83]. Optimal network and gain design to improve the convergence rate and error variance are interesting topics for the extension of this research. Recall that for the constant output matrix given in Section II-B, the LMI gain design is done only once and there is no need for multi-gain LMI design as in [85].

In target tracking, similar to general sensor network applications, sensor failure is typical and may affect the distributed estimation/tracking performance [86]. Further, packet dropout and lost information are also prevalent in such scenarios. To design a resilient protocol, the concept of $q$-redundant observability [87], [88] is relevant to designing $q$-redundant distributed estimators. In other words, we can design a network of UAVs that tolerates removal or failure of (less than or equal to) $q$ number of UAVs without losing its tracking stability performance. Similarly, one may add redundant links to the communication network of UAVs to preserve observability despite missing information and lost connections. The notion of $k$-connected networks and Menger’s theorem are relevant here. A network remains $k$-edge-connected (or $k$-node-connected) if it remains connected after removal of fewer than $k$ edges (or nodes) [89]. In fault-tolerant applications, this is referred to as survivable network design [65]. Recall that, from Theorem 1, SC-connectivity of $G_W$ (irreducibility of $W$) is sufficient for structural $(W \otimes F, D_H)$-observability. Therefore, designing $q$-edge-connected $G_W$ ensures that the target remains observable at all UAVs in case of up-to $q$ lost-links/missed-packets over the network. There exist efficient approximate algorithms for such survivable network design [66]. Similarly, $q$-node-connected $G_W$ ensures target observability despite (up-to) $q$ failed sensors, however, this is more relevant in static sensor networks (not the formation-tracking setup in this paper).\(^7\) In our tracking setup, resiliency may also refer to tracking in spite of missing the beacon signal information. In this perspective, some redundant agents (or sensors) with no measurement can be considered which play no crucial roles in the distributed estimation process, referred to as the Type-$\gamma$ agents in [49].

Remark 2: For (centralized) localization and in multilateration, the information of (at least) three UAVs is required to exactly locate the target [36], [70]. However, in this work, we only assume the multi-UAV network to be SC, implying that some UAVs may only have one (or two) neighbors. Recall that the strong-connectivity of the network implies that the information (on the target’s location) will eventually reach every other UAV over time (at most after $d$ time-steps where $d$ is the network diameter). This implies that after $k > 3$ every UAV receives the information of (at least) 3 other UAVs and therefore can localize the target using the protocol (12)-(13).

Remark 3: The cost-optimal design of a network subject to strong-connectivity is known as the minimum spanning strong subdigraph problem and is generally NP-hard [80]. However, under certain relaxations, for example, considering bidirectional links among the nodes (UAVs), the problem is known to have a polynomial-order solution. In this direction,

\(^6\) A matrix is irreducible if it is not similar via a permutation to a block upper triangular matrix (that has more than one block of positive size). Define similarity of two matrices $A$ and $B$ as the existence of an invertible matrix $P$ such that $B = P^{-1} A P$.

\(^7\) For the failure-resilient and fault-tolerant case, only sensor network aspect, and not necessarily the formation setup, is discussed in this paper. Resilient formation (with respect to node removal) is another topic of interest not in the scope of this paper.
the results in [80], [90]–[92] can be used to optimally design the SC network of UAVs under communication-cost constraints.

Remark 4: It is known that distributed algorithms are typically robust to single-node-of-failure and also scalable [86], which is also the case in this work. In case of damage (or failure) of any UAV or addition of new UAVs, the group can still perform the estimation/tracking over the network as long as Theorem 1 is not violated, i.e., the network is SC.

Remark 5: The proposed STS networked estimator is more desirable in real-time settings with power constraints and restricted communication budget as compared to MTS scenarios [39]–[43]. This estimator, further, outperforms the existing protocols [29]–[36] in terms of observability constraints. Note that, the typical approach in the literature assumes observability in the neighborhood of each UAV. This implies connectivity to (at least) 3 neighboring UAVs for stable estimation [36], while in this work the connectivity requirement is more relaxed to an SC network while the UAVs.

Remark 6: Other than the NCV model in Section II, for the maneuvering target, one may consider discrete-time correlated random walk (DCRW) [68], Nearly-Constant-Acceleration (NCA), and similar models discussed in [2], [67]. For any model with a (full-rank) F matrix and a measurement matrix H which renders observability (as is necessary for any estimation scenario), one can design (W ⊗ F, D_H)-observable networks from Theorem 1. The gain K can be designed similarly via LMI in [49], [83]. Then, the proposed protocol (12)-(13) can be used for any such F, H, and K matrices.

V. Formation Scenario

The group of UAVs is considered to form a formation on the XY-dimensions and then dynamically track the target. This helps to keep the target in the sensing range of the UAVs while fixing the UAVs’ mutual distances. In this section, the formation formulation regards only the i-th and j-th UAVs, while fixing the UA Vs’ mutual distances. In this section, the virtual target works as the collective column vector

\begin{align}
\bar{p}_i(k) &= \bar{p}_i(k-1) + T \bar{q}_i(k-1) + T \bar{v}_i(k-1), \\
\bar{q}_i(k) &= \bar{q}_i(k-1) + T \sum_{j \in N_i} U_{ij} \left( \frac{\bar{p}_{j,i}(k)}{\|\bar{p}_{j,i}(k)\|} + \frac{\bar{p}(k) - \bar{p}_i(k)}{\|\bar{p}(k) - \bar{p}_i(k)\|} \right) - T \bar{u}_i \sigma(\bar{q}_i(k-1)),
\end{align}

where \( \bar{v}_i \) is the velocity of the target estimated by UAV i, \( \bar{u} > 0 \), \( U_{ij} = \bar{p}_{j,i} - \bar{p}_i \) is the relative position vector between i-th and j-th UAVs, \( \sigma(x) = x / \sqrt{1 + \|x\|^2} \), and

\begin{align}
U_{ij} := \frac{\bar{u}_i}{\|\bar{p}_{j,i}(k)\|} (\bar{p}_{j,i}(k) - \bar{d}_{ij}) + \frac{\bar{u}_i}{\|\bar{p}(k) - \bar{p}_i(k)\|} (\bar{p}(k) - \bar{p}_i(k) - \bar{d}_i),
\end{align}

where \( \bar{d}_{ij} \) is the velocity of the target estimated by UAV i. To prove convergence of the virtual target, one may consider discrete-time correlated random walk, say located at the origin and \( p(k) = [0; 0] \) in (21). This is only for the sake of rigid formation coordination before they start tracking the target. Then, for tracking, this virtual target goes towards the estimated position of the real mobile target, and thus, UAVs move along with it (while keeping their formation). To improve the formation rigidity and guarantee global convergence, we mix the distance-based (DB) strategy with a barycentric-coordinate-based (BCB) solution [57], [94]. Define the BCB control input as,

\begin{align}
u_i = \sum_{j \in N_i} A_{ij} (p_j - p_i) = \sum_{j \in N_i} A_{ij} p_{j,i},
\end{align}

with anti-symmetric matrix \( A_{ij} \) defined as,

\begin{align}
A_{ij} = \begin{pmatrix} a_{ij} & b_{ij} \\ -b_{ij} & a_{ij} \end{pmatrix}, \quad a_{ij}, b_{ij} \in \mathbb{R}.
\end{align}

Then, substituting (24) in the dynamics associated with UAVs’ position dynamics \( \dot{p}_i = u_i \), the closed-loop collective dynamics at all UAVs is in the form \( \dot{p} = \dot{p}_i \) with \( p = [p_1; p_2; p_3; \ldots; p_N] \) as the collective column vector of UAVs’ positions in 2d space and 2N-by-2N collective gain matrix \( A \) (in block-Laplacian structure form) defined as,

\begin{align}
A = \begin{pmatrix}
A_{12} & \ldots & A_{1N} \\
A_{21} & -A_{12} & \ldots & A_{2N} \\
\vdots & \vdots & \ddots & \vdots \\
A_{N1} & A_{N2} & \ldots & -A_{N2} & \ldots & -A_{NN}
\end{pmatrix},
\end{align}

where \( A_{ij} = 0_{2 \times 2} \) for \( j \notin N_i \). For the collective dynamics, one can prove convergence globally to the desired shape [57, Appendix]. However, the drawback of this BCB strategy is that the formation scale cannot be controlled, and thus, it is combined with our DB method. Therefore, we modify (20) as,

\begin{align}
\dot{p}_i(k) = p_i(k-1) + T \epsilon_d q_i(k-1) + T \bar{v}_i(k-1) + T \epsilon_b u_i,\quad i = 1, \ldots, N,
\end{align}

with \( u_i \) as the i-th entry pair of \( \dot{p} \) in MATLAB code and \( \epsilon_d \) and \( \epsilon_b \) are...
Fig. 3. This figure shows the formation of 8 UAVs under 4 different scenarios over the XY-plane. The network $G_D$ of UAVs is connected with bidirectional links (solid black lines), which satisfies the conditions for steady-state stability of the tracking error. The UAVs keep their formation and their distance to other UAVs while keeping their distance (dashed blue lines) to the virtual target in the center (gray node). The target plays the role of a leader and the UAVs are the followers. For the case of mobile target tracking, the distance based V-shaped and distance + barycentric-coordinate based polygon-shaped formations (second left and last right figures) showed better rigidity performance, and thus, are used for the tracking simulations. The unit of distance ($p^x$, $p^y$ positions) in all figures is m.

VI. SIMULATION

A. Simulation Results of This Work

For the simulation, we consider a group of 8 UAVs tracking a mobile target with the NCV dynamics (1)-(3), sampling time $T = 0.12$, measurement noise $r = N(0, 0.0007)$, and $-0.15 \leq w \leq 0.15$ (uniformly distributed). The initial state (location and velocity) of the target is $x_0 = (2; 1; 2; 0; 0; 0)$. The initial locations (XY-coordinates) of the UAVs are $p^x_i = [2.2, 1.2, 0.1, 2.2, 2.7, 4.3]$ and $p^y_i = [-2.3, -1.2, 0.2, 1, 2, 1, 0.2, -1]$. The z positions are considered initially V-shaped in the range [0 1]. The formation parameters in Eq. (20)-(22) for DB V-shaped formation are: $d_{ij} = 1.9$ ($j \in N_i$), $\lambda_1 = \lambda_2 = 0.5$, $\bar{u} = 1$; and for DB plus BCB polygon-shaped formation in Eq. (23)-(26): $d_{ij} = 3.8$ ($j \in N_i$), $\lambda_1 = \lambda_2 = 0.5$, $\bar{u} = 1$, $\varepsilon_b = 0.25$, $\varepsilon_d = 0.75$, and $A_{ij} = \begin{pmatrix} 0 & 1.47 \\ -1.47 & 0 \end{pmatrix}$.

Different formation scenarios via these parameters are shown in Fig. 3. A rigid formation design fixes the UAVs’ distances over the communication network (as an undirected cycle); then, the gain matrix $K$ can be designed for each case via the algorithm in [49], [83], and is constant for the fixed formation. The UAVs first reach the specified formations (V-shaped or polygon) in Fig. 3; then, the tracking scenario starts. Each UAV receives the beacon signal from the target and shares the estimated target position along with its TDOA measurement (according to (6)-(10)) with its neighbors over the cyclic multi-UAV network in Fig. 3. Distributed estimation follows from Eq. (12)-(13) using random (but row-stochastic) consensus-fusion matrix $W$ associated with the cyclic network (irreducible matrix). The estimation error follows Eq. (17)-(18). For the $W$ and (designed) $K$ matrices in this simulation, the spectral radius of the closed-loop error dynamics in Eq. (19) is 0.98. In the noise-free scenario, this implies (approximate bound on) the convergence rate (of the observer) as $\frac{\varepsilon_b}{\varepsilon_d} < 0.98$ (see [84] for details). The trajectory of the target in 3D space and all the 8 UAVs (in formation) are shown in Fig. 4. The two formation scenarios shown in second left and last right in Fig. 3 are used for the tracking.
The Monte-Carlo simulation (50 trials) of the Mean-Square-Estimation-Error (MSEE), averaged at all 8 UAVs, is shown in Fig. 5(left) as compared with other methods.

### B. Comparison With Related Literature

As mentioned before, the approach in this paper differs from the literature in terms of the connectivity requirement of communication networks (for estimation irrespective of the formation). The centralized tracking literature, e.g. [21], [22], [25], requires an all-to-all communication network (among all 8 UAVs) where every UAV works as a data fusion center receiving the information from all other UAVs. In the decentralized case, e.g. [29]–[31], [33], [35], [36], [47], [49], every UAV requires the information of at least 3 neighboring UAVs. Thus, in this case, in the communication network in Fig. 3, every UAV requires an additional communication link from at least one more UAV (e.g., the 2nd nearest neighbor). From Fig. 3, this additional linking requires communication from a more distant UAV, and thus, necessitates more range of the communication devices on the UAVs. Thus, both communication traffic and communication range must be increased. Otherwise, the local observability condition is not satisfied, and thus, the given connectivity in Fig. 3, does not result in an observable estimation/tracking. In other words, for the mentioned references, under the connectivity given in Fig. 3, the MSEE goes unbounded due to the unobservability of the target. This shows the superiority of our proposed method over decentralized solutions, particularly when the communication range/load of the UAVs is limited. Among the existing works, the MTS protocols [41]–[43] have similar observability and connectivity requirements as our work, however, with a much faster communication rate requirement. The existing estimation/filtering scenarios are further compared in Table I. As it is clear, the proposed STS estimation (12)-(13) outperforms the centralized solutions and existing distributed solutions with local observability assumption in terms of the number of communication links, and improves the consensus-based MTS methods in terms of required communication rate.

1) Multi-Time-Scale: Recall that, from Section III, Fig. 2, and Table I, in MTS scenario the UAVs need to perform $L$ iterations of consensus-fusion between two consecutive time-steps $k$ and $k+1$ of target dynamics. We simulated the protocol in [42], [43] with $\alpha = 0.5$, $\beta = 0.5$, and $k_{sat} = 1$, for $L = 5, 10, 20$ in Fig 5. As claimed in [42], [43], the error performance and convergence rate closely depend on $L$ to be sufficiently large. For this scenario, UAVs need to share data and perform consensus $L = 5, 10, 20$ times faster than the sampling rate of the target dynamics (and the step rate of our proposed protocol). This certainly mandates more costly communication/computation accessories to be embedded at the UAVs. We compared the consensus and processing rate of our method (STS with global observability assumption) with other relevant scenarios in Table I. Note that the local observability assumption on UAVs requires (at least) $3N = 24$ directed links (or 12 bidirectional communications). The MTS method, on the other hand, requires $N(N-1) \times 1$ for $L$ times faster communication and consensus rate.

2) Centralized: For centralized solution, an all-to-all communication network makes the target dynamics locally observable to all UAVs via the shared measurements (no consensus iteration is involved). The MSEEs are compared in Fig. 5(right) for linear Kalman Filter (KF), Extended Kalman Filter (EKF), and Extended Rauch-Tung-Striebel (ERTS) smoother described in [95], [96]. For nonlinear filtering, the nonlinear measurement model (11) is used for simulation as in [6], [36], [68], [95], while our proposed linearized measurement model (8)-(10) is used for KF (and also for our STS method and the MTS method [42], [43]). From Fig. 5(right), clearly the MSEE performance of the linear measurement model (for KF) is quite comparable to the nonlinear filtering and measurement model (11). This further supports the measurement (8)-(10) used for distributed estimation.

**TABLE I**

| method/time-scale | observability | communication×rate | consensus |
|-------------------|---------------|---------------------|-----------|
| distributed/single| global        | $N \times 1$        | 1         |
| distributed/single| local         | $3N \times 1$       |           |
| distributed/multi | global        | $N \times L$        | $L$       |
| centralized       | -             | $N(N-1) \times 1$   | -         |
Recall that the distributed solutions in Fig. 5 (left and middle) use reduced network connectivity, while the centralized solutions use all-to-all network with certainly more measurement information available, and thus, better MSEE performance (right figure). Our proposed distributed method renders acceptable MSEE performance over such a sparsely-connected network, partially due to the rigid formation fixing the distances among the UAVs and using a precise modified linear model (8)-(10) vs. the nonlinear model (11).

VII. CONCLUSION AND FUTURE RESEARCH

A. Conclusion
This paper proposes a new target tracking approach via STS networked estimation with no assumption on local observability. Group of UAVs share information on the TOA of received beacon signals from the target along with a-priori estimates, and process these data via a twofold networked estimation: (i) consensus on a-priori estimates, and (ii) measurement-update. The proposed solution is of polynomial-order computational complexity; more complexity details of the distributed estimator can be found in [49], formation complexity in [18], [37], [56], [58], and complexity of the cone-complementary algorithms for the LMI gain design in [50].

B. Future Research Directions
Our ongoing research is focused on distributed estimation in presence of faults/attacks [50], [51], long-delayed communications among UAVs [84], [97], [98], and displacement-based formation scenarios [59]. One may also consider optimizing the memory and amount of stored/buffered data in case of latency [35]. Improving the convergence rate and error variance, e.g., by optimal design of the weight matrix $\mathbf{Q}$ and the communication network, are other promising directions. One can further consider distributed algorithms for local optimization [99], [100] over the multi-UAV network. It should be noted that the proposed distributed tracking is not restricted to the NCV target model; other target models, discussed in Remark 6 and [2], [67], can also be considered similarly.

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