Linear TDOA-based Measurements for Distributed Estimation and Localized Tracking

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Abstract—We propose a linear time-difference-of-arrival (TDOA) measurement model to improve distributed estimation performance for localized target tracking. We design distributed filters over sparse (possibly large-scale) communication networks using consensus-based data-fusion techniques. The proposed distributed and localized tracking protocols considerably reduce the sensor network's required connectivity and communication rate. We, further, consider \( \kappa \)-redundant observability and fault-tolerant design in case of losing communication links or sensor nodes. We present the minimal conditions on the remaining sensor network (after link/node removal) such that the distributed observability is still preserved and, thus, the sensor network can track the (single) maneuvering target. The motivation is to reduce the communication load versus the processing load, as the computational units are, in general, less costly than the communication devices. We evaluate the tracking performance via simulations in MATLAB.

Index Terms—Networked Estimation, TDOA measurements, \( \kappa \)-redundant distributed observability, fault-tolerant design

I. INTRODUCTION

Localized tracking and distributed estimation is considered in this paper to track a moving target via some static sensors, for example, tracking a rocket, a drone/UAV, or an airplane. Distributed estimators (or filters) has recently gained significant interest in signal processing, control, and machine learning literature to avoid single-node-of-failure\textsuperscript{1} and localize the computation and data processing\textsuperscript{2}–\textsuperscript{5} based on consensus algorithms\textsuperscript{6}. This is further motivated by the recent advancement in parallel processing, cloud computing, the Internet of Things (IoT), and wireless communication networks. The existing distributed methods are mainly based on consensus data-fusion and are categorized as either single-time-scale (STS) or double-time-scale (DTS) methods, based on their communication/consensus time-scale with respect to the target dynamics. The STS methods\textsuperscript{4}, \textsuperscript{5}, \textsuperscript{7}, \textsuperscript{8} perform one step of consensus at every time step of system (target) dynamics (the same time-scale), while the DTS methods\textsuperscript{9}–\textsuperscript{12} perform many iterations of consensus fusion between two consecutive time-steps of the dynamics, see the differences in\textsuperscript{13}, Fig. 1. These distributed strategies are mainly developed over linear and partially observable (measurement/system) models, e.g., for model-based and kinematic-based vehicle speed estimation\textsuperscript{14}. In this direction, the nonlinear range-based methods as TDOA\textsuperscript{4}, \textsuperscript{5}, \textsuperscript{15}, are linearized to be adapted for distributed setups. Such a linearization, in general, degrades the performance of the estimation while resulting in a time-varying output matrix and, in turn, a time-varying feedback gain. This requires redesigning the gain matrix at every iteration, e.g., via the iterative linear-matrix-inequalities (LMI) design\textsuperscript{16}, \textsuperscript{17}, and imposes more computational loads on the sensors. For practical target tracking applications, we need networked estimation scenarios with less communication and computational load on sensors, both in terms of communication traffic (networking) and data exchange rate. This plays a key role in real-time tracking of long-range maneuvering targets; see a survey in\textsuperscript{18}. Another challenge is to develop fault detection and isolation (FDI) algorithms for the distributed estimation networks, i.e., a joint distributed estimation and localized FDI setup\textsuperscript{19}, \textsuperscript{20}. A survey of security measures for the centralized observer design, with applications to intelligent transportation systems and tracking, is discussed in\textsuperscript{21}, \textsuperscript{22}.

Main contributions: We propose a new linear TDOA-based measurement model, in contrast to existing nonlinear counterparts. Recall that such nonlinear models, although acceptable in the centralized setup, need to be linearized for most distributed protocols. We compare the performance of the proposed linear model for modified TDOA with the existing nonlinear one, e.g., in\textsuperscript{4}. Linearization of such models may significantly reduce the performance of distributed tracking due to inaccurate measurements. Another reason for the inaccuracy is that the output matrix in the linearized model is also a function of the target position to be estimated. The proposed distributed estimator in this paper only requires distributed observability in contrast to local observability in the existing STS\textsuperscript{4}, \textsuperscript{5}, \textsuperscript{7}, \textsuperscript{8} and MTS\textsuperscript{9}–\textsuperscript{12} methods. This reduces (i) required communication traffic and linking over the network for the STS scenario and (ii) the required communication and consensus rate for the MTS models. The proposed method, further, can be improved by designing \( \kappa \)-redundant distributed observers, which are resilient to the removal (or failure) of up-to \( \kappa \) nodes (sensors) or links (communications) over the network. Moreover, localized distributed fault detection can be applied to this model to isolate possible faulty measurements over the sensor network. Thus, the proposed STS estimation and fault detection methodology are localized and do not need any centralized processing or decision-making unit, which is of interest in large-scale applications over faulty environments.

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Organization: The setup for the target tracking is discussed in Section II. The proposed distributed estimation along with the fault-detection setup are discussed in Sections III and IV. Sections (V) and (VI) provide the simulations and conclusions.

II. THE FRAMEWORK

We model the target based on the nearly-constant-velocity (NCV) model. This formulation is widely used in the literature, e.g., see [4], [5], [23], [24], representing a linear integrator model as,

\[ \mathbf{x}(k + 1) = F \mathbf{x}(k) + G \mathbf{w}(k) \]  

with state-vector \( \mathbf{x} = (p_z; p_y; p_z; p_y; p_z) \) as the position and velocity of the target in 3D space at time \( k \) (";" as the column concatenation), \( \mathbf{w}(k) = \mathcal{N}(0, Q) \) as some random input, and \( F \) and \( G \) respectively representing the transition and the input matrix defined as [23],

\[
F = \begin{pmatrix}
I_3 & T I_3 \\
0_3 & I_3
\end{pmatrix},
G = \begin{pmatrix}
T^2 I_3 \\
T I_3
\end{pmatrix}
\]  

with \( T \) as the sampling period, and \( I_n \) and \( 0_n \) as the identity and 0 matrix of size \( n \). The model can be simply extended to the nearly-constant-acceleration (NCA) model or any other target dynamics model (see [24] for more examples).

We consider a network of \( N \) sensors with position of sensor \( i \) denoted by \( \mathbf{p}_i = (p_{ix,i}; p_{iy,i}; p_{iz,i}) \) where the sensors are not located on the same \( x, y, z \) plane. Each sensor receives a beacon signal with known propagation speed \( c \) from the mobile target at every time \( k \) and computes the time-of-arrival (TOA) measurement (or range) based on \( \| \mathbf{p}(k) - \mathbf{p}_i(k) \| = ct_i \) (\( \| \cdot \| \) as the 2-norm) and shares this information, along with its position information, with the set of its direct neighboring sensors \( \mathcal{N}_i \). Overall, each sensor possess a list of TOAs and positions of the neighboring sensors, in the centralized setup the sensors share their information with many other sensors (e.g., an all-to-all network). In the existing literature, each sensor \( i \) performs filtering based on its nonlinear TOA measurement vectors as,

\[
y_i(k) = h_i(k) + \nu_i(k) \]  

\[
h_i(k) = (h_{i,j_1}(\mathbf{x}(k)); \ldots; h_{i,j_{|\mathcal{N}_i|}}(\mathbf{x}(k))) + \nu_i(k) \]  

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

i.e., subtracting the TOAs of its neighbors \( \{j_1, \ldots, j_{|\mathcal{N}_i|}\} \) from its own TOA (with additive Gaussian measurement noise \( \nu_i(k) = \mathcal{N}(0, R) \)). See Fig. 1 for more illustrations. In this paper, we first improve the proposed nonlinear measurement model (3)-(5), and provide a linear TOA measurement model to be used in distributed estimation and filtering. Then we propose a distributed estimator (along with localized fault detection strategy) to track the target via a sensor network with no need for local observability of the target in the neighborhood of any sensor (this is referred to as \textit{distributed observability} [25]). Further, \( \kappa \)-redundant estimator design and local fault-detection and isolation (FDI) are also considered.

III. THE PROPOSED DISTRIBUTED SETUP

For existing linear distributed estimation methods, the nonlinear measurement model (3)-(5) needs to be linearized as,

\[
y_i(k) = H_i(k) \mathbf{x}(k) + \nu_i(k), \]  

\[
H_i(k) = \begin{pmatrix}
\frac{\partial h_{i,j_1}}{\partial p_{x_1}} & \frac{\partial h_{i,j_1}}{\partial p_{y_1}} & \frac{\partial h_{i,j_1}}{\partial p_{z_1}} & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
\frac{\partial h_{i,j_{|\mathcal{N}_i|}}}{\partial p_{x_{|\mathcal{N}_i|}}} & \frac{\partial h_{i,j_{|\mathcal{N}_i|}}}{\partial p_{y_{|\mathcal{N}_i|}}} & \frac{\partial h_{i,j_{|\mathcal{N}_i|}}}{\partial p_{z_{|\mathcal{N}_i|}}} & 0 & 0
\end{pmatrix}, \]  

where,

\[
\frac{\partial h_{i,j}}{\partial p_{x_i}} = \frac{p_x - p_{x,i}}{\| \mathbf{p} - \mathbf{p}_i \|} - \frac{p_x - p_{x,j}}{\| \mathbf{p} - \mathbf{p}_j \|}, \]  

\[
\frac{\partial h_{i,j}}{\partial p_{y_i}} = \frac{p_y - p_{y,i}}{\| \mathbf{p} - \mathbf{p}_i \|} - \frac{p_y - p_{y,j}}{\| \mathbf{p} - \mathbf{p}_j \|}, \]  

\[
\frac{\partial h_{i,j}}{\partial p_{z_i}} = \frac{p_z - p_{z,i}}{\| \mathbf{p} - \mathbf{p}_i \|} - \frac{p_z - p_{z,j}}{\| \mathbf{p} - \mathbf{p}_j \|}. \]  

Note that all the parameters of the above measurement (output) matrix \( H_i \) depend on the target position \( \mathbf{p} \). Recall that, since the exact position of the target \( \mathbf{p} \) needs to be estimated by sensors (and is unknown), instead the estimated position \( \hat{\mathbf{p}}_i \) by each sensor \( i \) is used in (5) for the feedback gain design in [4], [5]. This, in turn, adds more uncertainty and accentuates the error of the linearized model. We dropped the dependence on time \( k \) only for notation simplicity. To provide a more accurate \textit{linear} model for distributed estimation methods and localized tracking applications we propose the following (instead of (5)),

\[
h_{i,j}(\mathbf{x}(k)) = \frac{1}{2} \left( \| \mathbf{p}(k) - \mathbf{p}_i(k) \|^2 - \| \mathbf{p}(k) - \mathbf{p}_j(k) \|^2 \right) \]  

\[
\approx \frac{1}{2} \left( (p_{x,j} - p_{x,i})(2p_x - p_{x,i} - p_{x,j}) + (p_{y,j} - p_{y,i})(2p_y - p_{y,i} - p_{y,j}) + (p_{z,j} - p_{z,i})(2p_z - p_{z,i} - p_{z,j}) \right) \]  

\[
= H_i (\mathbf{p}(k) - \frac{1}{2} (\mathbf{p}_j^2 - \mathbf{p}_i^2)) \]
where
\[ H_i = \begin{pmatrix} p_{x,1} & p_{y,1} & p_{z,1} & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{x,N_i} & p_{y,N_i} & p_{z,N_i} & 0 & 0 & 0 \end{pmatrix} , \]

Note that the above measurement model is linear with constant \( H_i \) for static sensors, which is an improvement over the linearized time-varying \( H_i \) in (7)-(10). Note that, from Fig. 1, \( p_{j,i} \) is fixed for two neighboring sensors \( j, i \). We specifically use this for our distributed estimation setup in the following.

For the linear target model (1)-(2) and measurements (11)-(14) we propose an STS networked estimator with consensus-fusion on prior estimates and innovation-update based on the measurement matrix \( H_i \) in (11)-(14) to get the posterior estimate. The proposed localized polynomial is,
\[ \hat{x}_i(k|k-1) = \sum_{j \in N_i} W_{ij} F \hat{x}_j(k-1), \quad j \in N_i \]
\[ \hat{x}_i(k) = \hat{x}_i(k|k-1) + K_i H_i^\top (y_i(k) - H_i \hat{x}_i(k|k-1)) , \]

with \( W_{ij} \) matrix representing the adjacency matrix of the communication network of sensors \( G \) (or the sensor network) and local gain matrix \( K_i \) to be designed later. Recall that for consensus-update the measurement matrix \( W \) needs to be further row-stochastic [16], [17]. \( \hat{x}_i(k) \) gives the (posterior) estimate of sensor \( i \) on the target state (position and speed), i.e., \( \hat{x}_i(k) = (\hat{p}_i; \hat{v}_i) \). It can be shown that the (collective) error dynamics for this estimator is in the form,
\[ e(k) = (W \otimes F - KD_H (W \otimes F)) e(k-1) + \eta(k) , \]

with block-diagonal matrices \( D_H := \text{diag}[H_i^\top H_i] \) representing the local feedback gains, and \( \eta \) collecting all the noise-related terms defined as,
\[ \eta(k) = 1_n \otimes G w(k-1) - K (1_n \otimes G w(k-1)) + \bar{D}_H \nu(k) \]
where \( \nu = (\nu_1; \ldots; \nu_n) \), \( 1_n \) is the column-vector of ones of size \( n \), and \( \bar{D}_H \triangleq \text{diag}[D_H] \) is defined as the block-diagonal matrix of all measurement matrices \( D_H \). Note that \( e(k) \) and \( \eta(k) \) represent the column concatenation of the local error terms as \( e(k) = (e_1(k); \ldots; e_n(k)) \) and \( \eta(k) = (\eta_1(k); \ldots; \eta_n(k)) \). From the Kalman stability theorem [26], error dynamics (17) is stabilizable if the pair \( (W \otimes F, D_H) \) is observable. This is known as distributed observability and implies observability over a network (associated with \( W \)). This is a much milder condition than the local observability needed in many STS distributed estimators, e.g., [8]. Following the structured systems theory, the error stability can be defined irrespective of the exact numeric of system entries and based on the zero-nonzero structure of matrices \( W, F, \) and \( H \).

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

Table I

| time-scale | filtering + detection | communication links × rate |
|------------|----------------------|---------------------------|
| STS        | ✓                    | \( 3(N - 1) \times 1 \)   |
| STS (this work) | ✓               | \( N \times 1 \)       |
| DTS        | ✓                    | \( N \times L \) with \( L \gg 1 \) |

IV. FAULT-TOLENT DESIGN

The next step is to locally detect and isolate possible measurement faults over the sensor network. In this case, consider potential additive faults at measurements as,
with \( f_i(k) \) denoting the fault-trend. Then, following the distributed FDI strategy in both stateless [30] and stateful setups [19], each sensor \( i \) can find possible faults at its measurements by monitoring its (absolute) instantaneous residual \( r_i(k) = |y_i(k) - C_i \hat{x}_i(k)| \) (stateless) or the history of its residuals (stateful). Probabilistic thresholds can be designed based on the statistics of the noise terms for both cases. For the stateless case, define the threshold for a given fault-alarm-rate (FAR) \( \alpha \) (see details in [30, Fig. 3]) as,

\[
\mathcal{T}_\alpha = \sqrt{2} \text{erf}^{-1}(\alpha) \Phi
\]

with \( \text{erf}^{-1}(\cdot) \) denoting the inverse Gauss error function and \( \Phi \) is defined (based on \( |\mathbb{E}(\eta_k \eta_k^T)\|_2 \)) approximately equal to [13], [31],

\[
\Phi \approx \|R\|_2 + \|H_i\|_2 a_1 N + \|Q\|_2 + \|\mathcal{R}\|_2 a_2 N^2
\]

where \( \mathcal{R} := \text{diag}(H_i^T R H_i) \), \( a_1 := \|N_i - KC_{Di}\|_2 \), \( a_2 := \|K\|_2 \), and some \( b < 1 \). For the threshold \( \mathcal{T}_\alpha \), if the residual \( r_i(k) > \mathcal{T}_\alpha \) the sensor raises the alarm and declares fault (with FAR less than \( \alpha \)). For the stateful case, first define the distance measure based on the residual history over a sliding time-window \( \theta \) as,

\[
z_i(k) = \sum_{m=k-\theta+1}^{k} \frac{(r_i(k))^2}{\Phi}, \quad k \geq \theta
\]

It can be shown that \( z_i(k) \) follows the \( \chi^2 \)-distribution [32]. Then, the threshold can be designed as [19],

\[
\mathcal{T}_\alpha = 2 \Gamma^{-1}(1 - \alpha, \frac{\theta}{2})
\]

with \( \Gamma^{-1}(\cdot, \cdot) \) denoting the inverse regularized lower incomplete gamma function. One can further design \( \kappa \)-redundant distributed estimators using the notion of \( \kappa \)-connected graph topology. Recall that a graph (network) is \( \kappa \)-edge-connected if it remains SC after removal of up-to \( \kappa \) links (i.e., any subset of links of size \( \kappa \)); similarly, it is \( \kappa \)-node-connected if it remains SC after removal of up-to \( \kappa \) (sensor) nodes (i.e., any subset of nodes of size \( \kappa \)). This is also referred to as survivable network design [32]. Note that this design procedure results from our distributed observability condition (instead of local observability), which only requires the strong connectivity of the network. To design a \( \kappa \)-connected sensor network, for example, the efficient algorithms in [33], [34] can be used.

Further, in the case of undirected networks (mutual linking among sensors), structural cost-optimal design of the sensor network can be considered to ensure a spanning tree (minimal connectivity) while optimizing the communication costs, e.g., see [35]; however, such a design problem is in general NP-hard for directed SC networks. Algorithm 1 summarizes our proposed methodology for distributed estimation (tracking), detection, and fault-tolerant design. To give an overview, the algorithm designs the network topology to fulfill (redundant) distributed observability, then uses TDOA measurements for distributed estimation; and finally, applies local detection techniques at every sensor.

Algorithm 1: distributed \( \kappa \)-redundant estimation and localized FDI.

1. **Input:** matrices \( F, G \) (or sampling period \( T \)), FAR \( \alpha \), redundancy factor \( \kappa \)
2. Design the networks \( \mathcal{G} \) (the sensor network) to be SC and \( \kappa \)-connected, e.g., via algorithms in [33], [34];
3. Calculate the TDOA measurement matrix \( H_i \) via (14) based on the relative positions of sensors;
4. Design the block-diagonal gain matrix \( K \) via LMI in [16, Appendix];

\begin{algorithm}
\begin{algorithmic}
\State **begin** sensor \( i = 1 : N \) at every time \( k \)
\State Receives estimates \( \hat{x}_{i-1|k}^t \) and TOAs \( \|p(k) - p_j(k)\| = ct_j \) from sensors \( \{j|i \in \mathcal{N}(j)\} \);
\State Finds the TDOA measurements via (11);
\State Finds the estimate \( \hat{x}_{i|k}^t \) via Eq. (15)-(16) on the target position (state) via the received information;
\State Finds the residual \( r_k^i \) or distance measure \( z_k^i \);
\State Finds the threshold \( \mathcal{T}_\alpha \) or \( \mathcal{T}_w \) for the FAR \( \alpha \);
\If {\( r_k^i > \mathcal{T}_\alpha \) or \( z_k^i > \mathcal{T}_w \)}
\State Sensor \( i \) raises the fault alarm (detection probability \( 1 - \alpha \));
\State Sensor \( i \) is isolated to avoid spread of the faulty measurement over the network;
\State The number of faulty sensors \( N_f = N_f + 1 \);\EndIf
\If {\( N_f \leq \kappa \)}
\State Distributed observability holds for tracking;
\Else
\State Distributed tracking is terminated;
\EndIf
\State **Output:** estimate of the target state \( \hat{x}_{i|k}^t \), fault decision at sensor \( i \), number of faulty sensors \( N_f \)
\end{algorithmic}
\end{algorithm}

V. SIMULATION

For the simulation, first, we compare the mean-square-error (MSE) performance of the proposed linear measurement model (11)-(14) with the linearized (nonlinear) model (7)-(10) using the Kalman Filter. We consider a sensor network of \( N = 10 \) sensors over an all-to-all communication network (the centralized tracking setup) for measurement and process noise \( w(k) = \mathcal{N}(0, Q_2 \mathbf{I}_n) \) and \( v = \mathcal{N}(0, R_2^2 \mathbf{I}_{N-1}) \) in (2) (with \( T = 0.1 \)). For the linearized model in [4], [5], we consider two cases: (i) using the exact target position \( p \) and (ii) using the estimated target position \( \hat{p} \) (which is used for the gain design). Note that the latter is only for the sake of comparison in terms of gain design accuracy in the distributed case. We consider the coordinates of the initial locations of the sensors and the target randomly in the range \([0, 10]\) and run the filter over 100 Monte-Carlo trials. The results are shown in Fig. 2. As it is clear from the figure, the proposed method considerably improves the MSE of the Kalman filter for higher process and measurement noise. Further, as discussed in Remark 1, in the distributed linearized setups the estimated position of the target is used in the output matrix \( H_i \) for practical gain
design, which further degrades the error stability performance due to additive uncertainty on $H_i$s.

On the same NCV setup, we provide MSE performance analysis of the proposed distributed STS estimator (15)-(16) in Fig. 3. The estimation error is bounded steady-state stable (averaged at all sensors) and unbiased in steady-state (the state errors at sensor 2 are shown as an example). The simulation is performed once over $\kappa = 2$-connected network and also over a simple cyclic network. Distributed observability is preserved after reducing the network connectivity to the cyclic network (which is SC) after removing (or missing) some (faulty) communication links (a survivable network design). The consensus fusion weights are random while satisfying stochastic property for consensus [36]. Note that, for each case, the local feedback gain is designed only once (using the LMI in [16, Appendix]) since the fusion weight matrix $W$ and the measurement matrix $H_i$ (given by (11)-(14)) are constant. This scenario is computationally more efficient (and more accurate) as compared to the repetitive gain design in [4], [5] which is performed at every iteration due to time-varying linearized $H_i$ in (7)-(10) (which is approximated by the estimated target position).

VI. CONCLUSION AND FUTURE DIRECTIONS

This paper provides a distributed (single-target) tracking with less communication and computational requirement than the existing (STS and DTS) methods. In some applications, one can extend the results to consider a rigid formation of leader-follower UAVs (and smart mobile sensors) [11], [37] to track a long-range maneuvering target (that may move out of the short-range of static sensors). Furthermore, the notions
of optimality and energy efficiency can be further addressed as future research directions to design minimal cost networks in terms of communication cost and energy consumption via the results in [27], [35], [38], [39]. Addressing delay-tolerant protocols is another promising research direction [40].

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