Distributed Sensor-Informative Tracking of Targets

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***Abstract*—In this work a distributed tracking technique for multiple non-overlapping targets is developed such that it utilizes only sensors that acquire informative observations about the targets. A framework is designed where norm-one regularized factorization is employed to decompose the sensor data covariance matrix into sparse factors whose support facilitates recovery of the target-informative sensors. Then, extended Kalman filtering recursions are derived to perform target tracking using only the target-informative sensors. Different from existing alternatives, the novel algorithm can determine the informative parts of the network topology without relying on underlying model parameters and target trajectory estimates, can handle multiple non-overlapping targets and is less sensitive to noise. Numerical tests corroborate the effectiveness of the proposed approach.**

I. INTRODUCTION

Sensor networks (SN) have been widely used in estimation and target tracking applications. Existing tracking techniques for SNs either require all sensors to be active [8], [12], or rely on the tracking algorithm position estimates along with the corresponding data and state model parameters to determine informative sensors for a single target [7]. Other related approaches emphasize more on determining sensor sleeping intervals and not tracking [4], [6], while [11] assumes the availability of the target position to activate sensors using tree-based structures in the network topology.

When targets are present in the sensed field, they are typically localized and affect only a small portion of the network, i.e., a small percentage of sensors will be located close to the targets and acquire informative measurements. Sensors, which are positioned close to a target, acquire measurements that tend to be correlated, no matter what the underlying physical model is. These properties give rise to a data covariance matrix that consists of approximately sparse factors. A distributed sparsity-cognizant framework is put forth to analyze the sensor data covariance into sparse factors whose support will point to the target-informative sensors. The latter task relies only on the available sensor measurements and different from [7] does not depend on model parameters and target position estimates that may not be accurate.

Extended Kalman filtering (EKF) recursions are derived to utilize only the informative sensor measurements to track the position of the present targets which are assumed to affect non-overlapping areas in the field. A robust interplay between distributed sparse covariance decomposition and EKF is proposed to perform tracking using only informative sensors. Numerical tests indicate that only a small part of the SN has to be active while closely tracking the field target(s).

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II. PROBLEM FORMULATION AND PRELIMINARIES

Consider an ad-hoc sensor network consisting of m sensors. Each sensor is able to communicate only with 'single-hop' neighbors that fall within its transmission range. The single-hop neighborhood for sensor j is denoted by $\mathcal{N}_j$, while inter-sensor links are symmetric and the SN is modeled as an undirected connected graph. Sensors acquire measurements about r moving targets in the sensed field. At time instant $t = 0, 1, 2, ...$, sensors acquire observations $x_j(t)$ for $j = 1 \ldots m$. This work focuses on i) identifying the sensors that acquire informative measurements about the targets; and ii) use the target-informative sensors to track the targets' position.

The sensor measurements adhere to the following model

$$\mathbf{x}_j(t) = \sum\nolimits_{\rho=1}^{r} a_\rho(t) d_{j,\rho}^{-2}(t) + w_j(t), \tag{1}$$

where i) $a_\rho(t)$ denotes the intensity of a signal emitted by the ρth target (e.g., as a result of a radar signal impinging on the target surface) and as targets are spatially separated, the intensity of the signals bouncing back from the target surfaces are assumed uncorrelated; ii) $d_{j,\rho}(t)$ denotes the distance between the ρth target and sensor j at time t, while the square exponent accounts for the power attenuation; and iii) $w_j(t)$ denotes the zero-mean white sensing noise with variance σ_w^2. The distance term $d_{j,\rho}(t)$ is equal to $\|\mathbf{p}_j - \mathbf{p}_\rho(t)\|$, where $\|\cdot\|$ denotes the Euclidean norm, $\mathbf{p}_j \in \mathbb{R}^{2\times 1}$ is the fixed and available position for sensor j, while $\mathbf{p}_\rho(t) := [p_{\rho,x}(t), p_{\rho,y}(t)]^T$ denotes the unknown ρth target position. The target state vector $\mathbf{s}_\rho(t)$ contains $\mathbf{p}_\rho(t)$ and the velocity $\mathbf{v}_\rho(t) := [v_{\rho,x}(t), v_{\rho,y}(t)]^T$, i.e., $\mathbf{s}_\rho(t) := [\mathbf{p}_\rho^T(t), \mathbf{v}_\rho^T(t)]^T$ and evolves according to

$$\mathbf{s}_\rho(t+1) = \mathbf{A}\mathbf{s}_\rho(t) + \mathbf{u}_\rho(t), \tag{2}$$

where $\mathbf{u}_\rho(t)$ denotes zero-mean Gaussian noise with covariance $\mathbf{\Sigma}_u$. The state model noise $\mathbf{u}_\rho(t)$ is assumed to be independent of the measurement noise, namely $\mathbf{w}_t := [w_1(t), \ldots, w_m(t)]^T$. The latter covariance matrix along with the common transition matrix $\mathbf{A}$ are given as

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \mathbf{\Sigma}_u = \sigma_u^2 \begin{bmatrix} T^3/3 & 0 & T^2/2 & 0 \\ 0 & T^3/3 & 0 & T^2/2 \\ T^2/2 & 0 & T & 0 \\ 0 & T^2/2 & 0 & T \end{bmatrix}$$

where T is the sampling period [1], and σ_u^2 a constant controlling the variance of the entries of the state noise. Emphasis is put onto developing a tracking scheme that is capable of identifying informative sensors in the SN. Thus, it is assumed that the r different target trajectories affect different non-overlapping regions of the SN, i.e., the sensors do not have to solve a multi-target data association problem (e.g., see [3]) that goes beyond the scope of the present work.

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Stacking the sensor measurements in a $m \times 1$ vector $\mathbf{x}_t$, it follows that $\mathbf{x}_t = \mathbf{B}_t\mathbf{a}_t + \mathbf{w}_t$, where $\mathbf{a}_t := [a_1(t)a_2(t)\dots a_r(t)]^T$ and $\mathbf{B}_t \in \mathbb{R}^{m\times r}$ has entries $\mathbf{B}_t(j,\rho) = d_{j,\rho}^{-2}(t)$, while the covariance of $\mathbf{w}_t$ is $\mathbf{\Sigma}_w = \sigma_w^2\mathbf{I}_m$ with $\mathbf{I}_m$ denoting the $m\times m$ identity matrix. Since the entries of $\mathbf{a}_t$ are uncorrelated it follows that the data covariance matrix is

$$\mathbf{\Sigma}_{x,t} = \mathbf{B}_t\mathbf{D}_a\mathbf{B}_t^T + \sigma_w^2\mathbf{I}_m = \bar{\mathbf{H}}_t\bar{\mathbf{H}}_t^T + \sigma_w^2\mathbf{I}_m, \tag{3}$$

where $\mathbf{D}_a$ is a diagonal matrix whose diagonal contains the variance of the entries in $\mathbf{a}_t$, while $\bar{\mathbf{H}}_t := \mathbf{B}_t\mathbf{D}_a^{1/2}$. Recall that $\mathbf{B}_t$ has entries $\mathbf{B}_t(j,\rho) = d_{j,\rho}^{-2}(t)$, thus if sensor j is located close to the ρth moving target at time t, then $\mathbf{B}_t(j,\rho)$ will have large amplitude, whereas if j is far from the ρth target then the corresponding entry will be close to zero.

Due to the locality of the targets a small number of sensors will be informative, and many entries in the columns of $\mathbf{B}_t$ will be relatively small making them approximately sparse (see also solid-green informative sensors in Fig. 2). Sparsity-aware distributed matrix decomposition techniques are combined with extended Kalman filtering to perform target tracking by utilizing only the target-informative sensors.

III. Distributed Sensor-Informative Tracking Algorithm (D-NIT)

Recall that determination of the sensors that acquire informative observations about the ρth target amounts to locating where the strong-amplitude entries are in the ρth column of $\mathbf{B}_t$, namely $\mathbf{b}_{\rho,t}$. Once the informative sensors are recovered, then pertinent EKF recursions will be applied among them.

A. Online Selection of Target-Informative Sensors

Let $\mathbf{S}_{x,t} := \mathbf{\Sigma}_{x,t} - \sigma_w^2\mathbf{I}_m = \bar{\mathbf{H}}_t\bar{\mathbf{H}}_t^T$, correspond to the noiseless signal covariance matrix. Also, notice that the indices of relatively small- and strong-amplitude entries in $\mathbf{b}_{\rho,t}$ and $\bar{\mathbf{h}}_{\rho,t}$ are identical since $\bar{\mathbf{h}}_{\rho,t} = \mathbf{D}_a^{1/2}(\rho,\rho)\mathbf{b}_{\rho,t}$. Thus, determination of target-informative sensors boils down to the task of recovering the approximately sparse factors $\bar{\mathbf{h}}_{\rho,t}$ whose support (indices of strong-amplitude entries) will indicate which sensors are relatively close to the ρth target.

In practice the time-varying ensemble covariance $\mathbf{\Sigma}_{x,t}$ is not known. Time-variation in covariance is caused by the targets whose changing position results a time-evolving $\bar{\mathbf{H}}_t$. Thus, the covariance matrix should be estimated in a way that relies more on new data while gradually discarding the old ones. A covariance estimate $\hat{\mathbf{\Sigma}}_{x,t}$ can be obtained using an exponentially-weighted averaging scheme as

$$\hat{\mathbf{\Sigma}}_{x,t} = \textstyle\sum_{\tau=0}^{t}\gamma^{t-\tau}\mathbf{x}_\tau\mathbf{x}_\tau^T, \tag{4}$$

and $\hat{\mathbf{S}}_{x,t} = (1-\gamma)(1-\gamma^{t+1})^{-1}\hat{\mathbf{\Sigma}}_{x,t} - \hat{\mathbf{D}}_w$, where $\hat{\mathbf{D}}_w := \text{diag}(\hat{\sigma}_{w,1}^2,\dots,\hat{\sigma}_{w,m}^2)$ while $\gamma \in (0,1)$ and $\hat{\sigma}_{w,j}^2$ denotes a noise variance estimate at sensor j obtained e.g., by averaging noisy measurements in the absence of targets. The scaling performed in $\hat{\mathbf{\Sigma}}_{x,t}$ when forming $\hat{\mathbf{S}}_{x,t}$ is done such that $(1-\gamma)(1-\gamma^{t+1})^{-1}\hat{\mathbf{\Sigma}}_{x,t+1}$ would be an unbiased estimate of $\mathbf{\Sigma}_{x,t}$ in a time-invariant setting.

A pertinent framework to recover the 'sparse' columns of the unknown $\bar{\mathbf{H}}_t$ (or $\mathbf{B}_t$) at time t relies on ℓ_1 (norm-one) regularization and involves the minimization problem [9]

$$\hat{\mathbf{H}}_t = \arg\min_{\mathbf{H}} ||\mathbf{E}\odot(\hat{\mathbf{S}}_{x,t} - \mathbf{H}\mathbf{H}^T)||_F^2 + \textstyle\sum_{\rho=1}^{r}\lambda_\rho||\mathbf{h}_\rho||_1, \tag{5}$$

where $\mathbf{E}$ denotes the adjacency matrix of the sensor network setting, while $\odot$ denotes entry-wise matrix product. The Frobenius term $\|\cdot\|_F$ in (5) can be rewritten as $\sum_{j=1}^{p}\sum_{j'\in N_j\cup j}(\hat{\mathbf{S}}_x(j,j') - \sum_{l=1}^{r}\mathbf{H}(j,l)\mathbf{H}(j',l))^2$ which entails only the entries $\hat{\mathbf{S}}_{x,t}(j,j')$ for $j\in\mathcal{N}_j$ that can be evaluated by sensor j after communicating with its neighbors in $\mathcal{N}_j$. Thus, adjacency matrix $\mathbf{E}$ is used to comply with the single-hop communication topology [9]. The ℓ_1 regularization term is widely used to effect sparsity, see e.g., [10].

Coordinate descent techniques [2, pg. 160] are utilized to derive an iterative distributed minimization algorithm [9], which minimizes the cost in (5) recursively wrt an entry of $\mathbf{H}$, while keeping the remaining elements in $\mathbf{H}$ fixed. During one coordinate descent cycle all the entries of matrix $\mathbf{H}$ are updated. Sensor j is responsible for updating the entries $\{\mathbf{H}(j,\rho)\}_{\rho=1}^{r}$. It turns out that (details in [9]) during coordinate cycle k, the update of the (j,ρ)-th entry of $\mathbf{H}$, namely $\hat{\mathbf{H}}_t^k(j,\rho)$, can be obtained as the value that achieves the minimum possible cost in (5) among the candidate values: i) $h=0$; ii) the real positive roots of the third-degree polynomial

$$\begin{aligned}4h^3 + 4[\textstyle\sum_{\mu\in\mathcal{N}_j}[\hat{\mathbf{H}}_t^{k-1}(\mu,\rho)]^2 - \delta_{t,S}^k(j,j,\rho)]h \\ + \lambda_\rho - [4\textstyle\sum_{\mu\in\mathcal{N}_j}\delta_{t,S}^k(j,\mu,\rho)\hat{\mathbf{H}}_t^{k-1}(\mu,\rho)] = 0;\end{aligned} \tag{6}$$

and iii) the real negative roots of the third-degree polynomial

$$\begin{aligned}4h^3 + 4[\textstyle\sum_{\mu\in\mathcal{N}_j}[\hat{\mathbf{H}}_t^{k-1}(\mu,\rho)]^2 - \delta_{t,S}^k(j,j,\rho)]h \\ - \lambda_\rho - [4\textstyle\sum_{\mu\in\mathcal{N}_j}\delta_{t,S}^k(j,\mu,\rho)\hat{\mathbf{H}}_t^{k-1}(\mu,\rho)] = 0,\end{aligned} \tag{7}$$

where $\delta_{t,S}^k(j,\mu,\rho) := \hat{\mathbf{S}}_{x,t}(j,\mu) - \sum_{\ell=1,\ell\neq\rho}^{r}\hat{\mathbf{H}}_t^{k-1}(j,\ell)$ $\hat{\mathbf{H}}_t^{k-1}(\mu,\ell)$. The roots can be obtained using, e.g, companion matrices [9]. Note that sensor j can evaluate the coefficients of the polynomials in (6) and (7) by exchanging information only with its neighbors in $\mathcal{N}_j$. Specifically, sensor j receives $\{\hat{\mathbf{H}}_t^{k-1}(\mu,1),\dots,\hat{\mathbf{H}}_t^{k-1}(\mu,r)\}$ from sensors $\mu\in\mathcal{N}_j$ and forms $\delta_{t,S}^k(j,\mu,\rho)$. Similarly, it transmits to its neighbors the r scalar updates for the jth row of $\mathbf{H}$, namely $\{\hat{\mathbf{H}}_t^{k-1}(j,1),\dots,\hat{\mathbf{H}}_t^{k-1}(j,r)\}$. To facilitate an online implementation a small fixed number, say K, of coordinate descent cycles is applied per time instant t. Pertinent techniques of choosing the sparsity-controlling coefficients λ_ρ that ensure recovery of the informative sensors can be found in [9]. The number of targets r does not have to be known a priori, an upper bound can be used instead while a deflation mechanism can be employed to estimate the sparse factors [9].

B. Extended Kalman Filtering

Once the target-informative sensors have been recovered using the framework in Sec. III-A, the next step is to use the target-informative observations, and the corresponding state and observations models in Sec. II to perform target tracking. Since the sensor measurements are not linearly related to the unknown target position, EKF recursions are derived [5].

Let $\mathcal{I}_{\rho,t}$ denote the recovered target-informative sensors at time t whose measurements are dominantly affected by the ρth target. One sensor within the sensor subset $\mathcal{I}_{\rho,t}$ is designated as a cluster head (see Sec. III-C), namely $C_{\rho,t}$. The r sensors $\{C_{\rho,t}\}_{\rho=1}^{r}$ collect only the informative observations $\mathbf{x}_{\mathcal{I}_{\rho,t}} := \{x_j(t)\}_{j\in\mathcal{I}_{\rho,t}}$ at t and combined with (1) and (2) carry out the EKF tracking recursions to track the trajectory of the ρth target. Let $\hat{\mathbf{s}}_\rho(t-1|t-1)$ denote the correction estimate for the true state $\mathbf{s}_\rho(t-1)$, and $\mathbf{M}_\rho(t-1|t-1)$ the corresponding correction mean-square error (MSE) matrix obtained by EKF at time instant $t-1$ using the informative-sensor measurements $\mathbf{x}_{\mathcal{I}_{\rho,\tau}}$ for $\tau = 0,\ldots,t-1$. Since the state model evolves linearly, the prediction state estimate $\hat{\mathbf{s}}_\rho(t|t-1)$ for $\mathbf{s}_\rho(t)$ using $\{\mathbf{x}_{\mathcal{I}_{\rho,\tau}}\}_{\tau=0}^{t-1}$ and the associated prediction MSE matrix $\mathbf{M}_\rho(t|t-1)$ can be obtained as [5, Chp. 13]

$$\hat{\mathbf{s}}_\rho(t|t-1) = \mathbf{A}\hat{\mathbf{s}}_\rho(t-1|t-1), \tag{8}$$

$$\mathbf{M}_\rho(t|t-1) = \mathbf{A}\mathbf{M}_\rho(t-1|t-1)\mathbf{A}^T + \mathbf{\Sigma}_u. \tag{9}$$

Cluster head $C_{\rho,t}$ can carry out the recursions in (8) as long as $\mathbf{A}$ and $\mathbf{\Sigma}_u$ are available across sensors, e.g., can be determined from the physics of the problem. The EKF correction recursions can be obtained after linearizing the observation model around the prediction estimate $\hat{\mathbf{s}}_\rho(t|t-1)$ [5]. Note from (1) that the informative measurements adhere to the model $\mathbf{x}_{\mathcal{I}_{\rho,t}} = \mathbf{B}_{\mathcal{I}_{\rho,t}}\mathbf{a}_t + \mathbf{w}_{\mathcal{I}_{\rho,t}}$, where $\mathbf{B}_{\mathcal{I}_{\rho,t}}$ and $\mathbf{w}_{\mathcal{I}_{\rho,t}}$ denote the matrix and vectors obtained after keeping only the rows and entries of $\mathbf{B}$ and $\mathbf{w}$ with indices in $\mathcal{I}_{\rho,t}$. Let $\mathbf{g}(\{\mathbf{s}_\rho(t)\}_{\rho=1}^{r}) = \mathbf{B}_{\mathcal{I}_{\rho,t}}\mathbf{a}_t$ denote the signal component in $\mathbf{x}_{\mathcal{I}_{\rho,t}}$ which depends on the target states $\mathbf{s}_\rho(t)$ due to the dependence of $\mathbf{B}_{\mathcal{I}_{\rho,t},t}$ on the target position $\mathbf{p}_\rho(t)$. Assuming that targets move in well separated non-overlapping areas, the observations $\mathbf{x}_{\mathcal{I}_{\rho,t}}$ will mainly be affected by the ρth target term $a_\rho(t)d_{j,\rho}^{-2}(t)$, while the other target terms in the sum in (1) will be negligible. The reason is that every sensor $j \in \mathcal{I}_{\rho,t}$ is positioned close to the ρth target and $d_{j,\rho'} \gg d_{j,\rho}$ for $\rho' \neq \rho$, i.e., $x_j(t) \approx a_\rho(t)d_{j,\rho}^{-2}(t) + w_j(t)$ for $j \in \mathcal{I}_{\rho,t}$. A first-order Taylor expansion of the observations $\{x_j(t)\}_{j\in\mathcal{I}_{\rho,t}}$ around the state prediction $\hat{\mathbf{s}}_\rho(t|t-1) = [\hat{\mathbf{p}}_\rho^T(t|t-1), \hat{\mathbf{v}}_\rho^T(t|t-1)]^T$ for the dominant ρth target at sensor j gives

$$\begin{aligned} x_j(t) \approx & a_\rho(t)\|\mathbf{p}_j - \hat{\mathbf{p}}_\rho(t|t-1)\|^{-2} + \\ & a_\rho(t)\nabla\mathbf{b}_{j,\rho}^T(\hat{\mathbf{s}}_\rho(t|t-1)) \cdot [\mathbf{s}_\rho(t) - \hat{\mathbf{s}}_\rho(t|t-1)] + w_j(t), \end{aligned} \tag{10}$$

where

$$\begin{aligned} \nabla\mathbf{b}_{j,\rho}(\hat{\mathbf{s}}_\rho(t|t-1)) &:= \frac{\partial \mathbf{B}(j,\rho)}{\partial \mathbf{s}_\rho(t)}\Big|_{\mathbf{s}_\rho(t)=\hat{\mathbf{s}}_\rho(t|t-1)} \\ &= 2\left[(p_{j,x} - \hat{p}_{\rho,x}(t|t-1))^2 + (p_{j,y} - \hat{p}_{\rho,y}(t|t-1))^2\right]^{-2} \\ &\quad \times [p_{j,x} - \hat{p}_{\rho,x}(t|t-1), p_{j,y} - \hat{p}_{\rho,y}(t|t-1), 0, 0]^T. \end{aligned} \tag{11}$$

The cluster head $C_{\rho,t}$ updates the correction state estimate $\hat{\mathbf{s}}_\rho(t|t)$ for state $\mathbf{s}_\rho(t)$ and the MSE matrix $\mathbf{M}_\rho(t|t)$ as

$$\hat{\mathbf{s}}_\rho(t|t) = \hat{\mathbf{s}}_\rho(t|t-1) + \mathbf{K}_\rho(t)(\mathbf{x}_{\mathcal{I}_{\rho,t}} - a_\rho(t)\hat{\mathbf{B}}_{\mathcal{I}_{\rho,t}}), \tag{12}$$

$$\mathbf{M}_\rho(t|t) = [\mathbf{I}_{4\times4} - \mathbf{K}_\rho(t)\mathbf{B}_\nabla(t)]\mathbf{M}_\rho(t|t-1), \tag{13}$$

in which $\hat{\mathbf{B}}_{\mathcal{I}_{\rho,t}}$ is the $|\mathcal{I}_{\rho,t}| \times 1$ vector with entries $\{\|\mathbf{p}_j - \hat{\mathbf{p}}_\rho(t|t-1)\|^{-2}\}_{j\in\mathcal{I}_{\rho,t}}$, $\mathbf{B}_\nabla$ is a $|\mathcal{I}_{\rho,t}| \times 4$ matrix with rows filled by the $\nabla\mathbf{b}_{j,\rho}^T(\hat{\mathbf{s}}_\rho(t|t-1))$ for $j \in \mathcal{I}_{\rho,t}$, whereas $\mathbf{K}_\rho(t) = \mathbf{M}_\rho(t|t-1)\mathbf{B}_\nabla^T(t)(\sigma_w^2\mathbf{I}_{|\mathcal{I}_{\rho,t}|} + \mathbf{B}_\nabla(t)\mathbf{M}_\rho(t|t-1)\mathbf{B}_\nabla^T(t))^{-1}$.

The EKF correction recursions (12) taking place at cluster head $C_{\rho,t}$ require availability of the target intensity signal $a_\rho(t)$ and the measurement noise variance σ_w^2. In practical settings if $a_\rho(t)$ is not available, an estimate $\hat{a}_\rho$ can be used instead for the expectation $E[a_\rho(t)]$. During a start-up phase each sensor j collects, say T_s, measurements $\{x_j(\tau)\}_{\tau=-(T_s-1)}^{0}$ sampled sufficiently fast such that the r targets' can be considered approximately immobile. Then, averaging the measurements of sensor j gives that for sufficiently large T_s the expectation $E[a_\rho(t)]$ can be estimated at sensor j as $\hat{a}_\rho^j \approx \|\mathbf{p}_j - \mathbf{p}_\rho(0)\|^2 T_s^{-1}\sum_{\tau=(1-T_s)}^{0} x_j(\tau)$. The unknown target position $\mathbf{p}_\rho(0)$ can be estimated using the 'average' location of the informative sensors, i.e., $\hat{\mathbf{p}}_\rho(0) = \sum_{j\in\mathcal{I}_{\rho,0}}\mathbf{p}_j$, at cluster head $C_{\rho,0}$. The estimate $\hat{\mathbf{p}}_\rho(0)$ is sent from $C_{\rho,0}$ to the sensors $\mathcal{I}_{\rho,0}$ which can then evaluate $\hat{a}_\rho^j$ and transmit it to $C_{\rho,0}$ that forms the estimate $\hat{a}_\rho = |\mathcal{I}_{\rho,0}|^{-1}\sum_{j\in\mathcal{I}_{\rho,0}}\hat{a}_\rho^j$. A sample-averaging based estimate for the noise variance σ_w^2 can be used as in Sec. III-A.

C. Joint Tracking and Sensor Selection

During the start-up phase the acquired sensor measurements $\{\mathbf{x}(\tau)\}_{\tau=-(T_s-1)}^{0}$ are used by the distributed sparsity-aware decomposition framework to determine the sets of informative sensors $\{\mathcal{I}_{\rho,0}\}_{\rho=1}^{r}$. One sensor in $\mathcal{I}_{\rho,0}$ will be designated as the cluster-head $C_{\rho,0}$ that collects from sensors $j \in \mathcal{I}_{\rho,0}$ the corresponding measurements $x_j(0)$. Cluster-head $C_{\rho,0}$ uses the average 'informative'-sensor location $\hat{\mathbf{p}}_\rho(0) = \sum_{j\in\mathcal{I}_{\rho,0}}\mathbf{p}_j$ to initialize the target position in the EKF. The scheme in Sec. III-A interacts with the EKF recursions leading to a distributed sensor-informative tracking (D-NIT) algorithm.

Suppose that at time $t-1$ each cluster head $\{C_{\rho,t-1}\}$ has available the EKF state predictions $\hat{\mathbf{s}}_\rho(t|t-1)$ for $\rho = 1,\ldots,r$. Each predicted target position $\hat{\mathbf{p}}_\rho(t|t-1)$ is utilized to select a set of 'candidate' informative sensors, namely $\mathcal{J}_{\rho,t}$, such that sensor $j \in \mathcal{J}_{\rho,t}$ if $\|\mathbf{p}_j - \hat{\mathbf{p}}_\rho(t|t-1)\| \leq R$. The radius R through which $\mathcal{J}_{\rho,t}$ are constructed is up to our control such that the selected sensors are single-hop neighbors, and the faster the target moves the larger should be chosen to ensure that all target-informative sensors are incorporated in $\mathcal{J}_{\rho,t}$. Not all sensors in $\mathcal{J}_{\rho,t}$ will be target informative. The distributed scheme in Sec. III-A is applied among the sensors in $\mathcal{J}_{\rho,t}$ to determine the target-informative sensor sets $\mathcal{I}_{\rho,t} \subseteq \mathcal{J}_{\rho,t}$ for $\rho = 1,\ldots,r$. Performing the sensor-selection process (Sec. III-A) in $\mathcal{J}_{\rho,t}$ requires less computational and communication complexity than when applied in the whole SN. The larger R is, the more probable is to recover all informative sensors.

The cluster-head $C_{\rho,t}$ is selected as the sensor in $\mathcal{I}_{\rho,t}$, which is closest to the predicted position of the ρ-th target and collects i) the prediction state estimate and MSE covariance $\hat{\mathbf{s}}_\rho(t|t-1)$ and $\mathbf{M}_\rho(t|t-1)$ from $C_{\rho,t-1}$; and ii) the sensors measurements $x_j(t)$ for $j \in \mathcal{I}_{\rho,t}$. Then, $C_{\rho,t}$ proceeds to update the correction and prediction state estimates $\hat{\mathbf{s}}_\rho(t|t)$, $\hat{\mathbf{s}}_\rho(t+1|t)$ as detailed in Sec. III-B. To ensure that all sensors in $\mathcal{I}_{\rho,t}$ can reach $C_{\rho,t}$ the transmission range of sensors further than two-hops away is increased such that they can access $C_{\rho,t}$ directly during the tracking phase.

Different from [7], the proposed informative sensor selection process here does not depend on the state and observation model parameters in (1) and (2), and relies on the sensor measurements to update the target-informative portion of the SN, and it is not affected by the EKF estimates. The approach for choosing active sensors in [7] relies on the prediction state estimate and MSE covariance obtained through EKF.

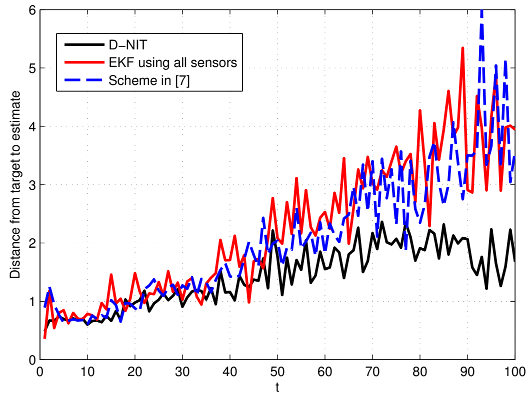

Fig. 1. Distance from target to estimate versus time.

Linearization in EKF may result errors in the tracking process which can propagate to the sensor selection process in [7] and deteriorate performance. In the same way, selecting the closest sensors to the estimated target position is prone to error propagation and cannot perform better than [7]. Further, in D-SMD, the communication cost at sensor S_j is linearly dependent on the number of single-hop neighbors $\mathcal{N}_j$, while in [7], all sensors send their data to the current cluster head, leading to a communication cost which is proportional to the total number of sensors m.

IV. Numerical Tests

Next, we test the tracking performance of D-NIT and compare it with existing alternatives. We consider a connected SN with $m = 100$ sensors randomly placed in the region $[0, 10] \times [0, 10]$. The sampling period $T = 1s$ and $\sigma_u^2 = 0.07$ in (3), while $\sigma_w^2 = 0.001$ in (1), and the target-intensity signals are Gaussian with $E[a_1(t)] = 1$ and $\mathrm{var}(a_1(t)) = 0.25$. The forgetting factor for updating $\hat{\mathbf{S}}_{x,t}$ is set to $\gamma = 0.1$. The sparsity-controlling coefficients in Sec. III-A are set as in [9]. The radius $R = 1.5$, while $T_s = 20$.

A setting with one target is considered first. We compare the tracking performance of D-NIT with a scheme that combines the sensor selection process in [7] with EKF. Different from [7], the novel approach in Sec. III-A does not rely on the model parameters in (1) and (2), and the EKF estimates. The target position is initialized as in Sec. III-C, while the speed is set $\hat{\mathbf{v}}_1(0|0) = [0.2\ 0.2]^T$ and $\mathbf{M}_1(0|0) = 50\mathbf{I}_4$. Fig. 1 depicts the distance error between the true and corrected position estimates versus time; averaged over 150 Monte Carlo trials. Fig. 1 depicts that as t increases the tracking error associated with D-NIT stabilizes, though [7] experiences fluctuations of increasing magnitude. The sensitivity of [7] during the EKF linearization step is clear. The comparison was done such that D-NIT and [7] have on average the same number of active sensors. The tracking performance achieved by D-NIT is also better than the standard EKF approach, where all $m = 100$ sensors are active. The reason is that D-NIT utilized only a few sensors at t, i.e., $|\mathcal{I}_{\rho,t}| < 8$, thus the linearization process is more robust since less noise (informative measurements have high SNR) is introduced. D-NIT achieves better performance while using less than 8% of the SN.

Next, a two-target scenario is considered. It should be mentioned that [7] cannot handle multiple targets even if they

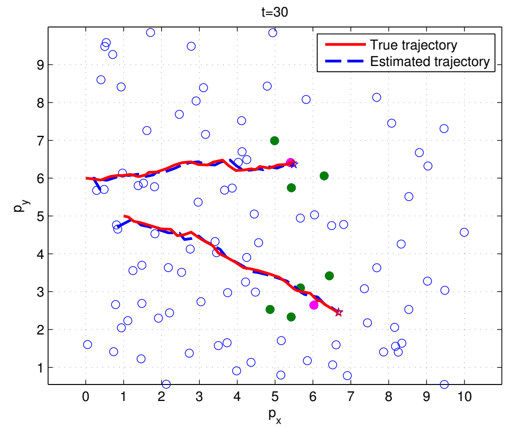

Fig. 2. Tracking two targets via D-NIT. Time instant $t = 30$s is depicted.

affect non-overlapping regions of the SN. Fig. 2 depicts the informative sensors associated with the two different targets at $t = 30$; $\sigma_u^2 = 0.002$ here. Clearly, the informative sensors (green and purple dots) are always close to the true position of the targets; the purple dots correspond to cluster heads. D-NIT is able to follow closely the two different tracks while using a small number of sensors.

V. Concluding Remarks

A distributed algorithm was put forth that performs target tracking while using only a few informative sensors in the SN. The task of determining target-informative sensors boils down to a distributed sparse matrix decomposition problem that is combined with EKF to track multiple targets moving in non-overlapping areas. Simulations show that the proposed technique achieves, even when using a few sensors, better performance compared to related alternatives.

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