DISTRIBUTED SPATIO-TEMPORAL MULTI-TARGET ASSOCIATION AND TRACKING

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ABSTRACT

Particle filtering is combined with sparse matrix decomposition techniques to address the problem of tracking multiple targets using nonlinear sensor observations measuring signal strength. The unknown number of targets may be time-varying, while sensors are spatially scattered. Norm-one regularized matrix factorization is employed to decompose the sensing data covariance matrix into sparse factors whose support facilitates the task of associating the targets with sensor measurements. The novel sensors-to-targets association scheme is developed using distributed optimization which is further integrated with particle filtering mechanisms to perform accurate tracking. Numerical tests demonstrate the tracking superiority of the proposed algorithm over alternative approaches.

Index Terms— Particle filtering, sensor-to-targets association, distributed processing, multi-target tracking.

1. INTRODUCTION

Sensor networks (SNs) allow the collection and distributed processing of information in challenging environments whose structure is not known and is dynamically changing with time, while multiple sources/targets may be present. A necessary step in multi-target tracking is the association of sensors with targets across space and time. Thus, it is pertinent to identify the sensors that acquire informative observations about the targets and use only those to perform tracking. We characterize such sensors as 'target-informative' sensors. Many existing tracking techniques require all sensors to be active [1,4,21,22] which may be resource-consuming given the locality of the targets and the fact that only a few sensors bear information about the field targets. A decentralized algorithmic framework is developed here that does not require a central fusion center and it can associate sensors with targets combined with tracking.

Single-target tracking techniques have been developed for SNs using consensus-averaging techniques [5, 17] combined with particle filtering, e.g., see [6]. Extended Kalman filtering (EKF) for tracking a single-target is combined with a probabilistic framework for selecting sensors in [16]. Existing multi-target tracking applications perform association in time to determine which measurements, gathered at a *single* sensor, contain information about a target [7, 9, 12]. Probabilistic models on the number of targets and the target-measurement assignments are also employed in [18] to perform multi-target tracking in single-sensor settings. Improved particle sampling techniques for single sensor settings are considered in [27], where particles corresponding to closely spaced targets are sampled jointly. The latter approaches require the availability of a probabilistic data model which is utilized to associate measurements acquired across time with the targets present. A centralized algorithm, that relies on Markov chain Monte Carlo (MCMC) tools, performs temporal data association on measurements acquired at a single-sensor across time in polynomial time [20]. The previous framework is extended to a network of sensors in [19].

An algorithmic framework is put forth here that associates targets with sensors that acquire informative measurements about these targets, and subsequently performs tracking using only these informative sensors. Existing association schemes [7, 9, 12, 18, 19, 26] match measurements with targets across time and utilize probabilistic models. Differently, the sensors-targets association task here is relying only on the sensor measurements and no probabilistic models are adopted. Another common assumption present in existing multi-target schemes, e.g., [7, 9, 12, 18, 19, 26], is that sensor measurements contain information about just *one* target. Here sensors may be sensing multiple targets at the same time among which one of them is closer to the sensor than the rest.

Our approach relies on the fact that sensors which are positioned close to the same target, acquire correlated measurements. Such correlations induce a sparse (presence of many zeros) structure in the sensor data covariance matrix. A pertinent framework is derived to decompose the sensing covariance into sparse factors whose support (position of the nonzero entries) will indicate subsets of sensors observing the same target. Different from [11, 15, 28], the matrix factorization scheme developed here does not require a central fusion center and does not impose structural requirements to the unknown factors such as orthogonality and/or positivity of the factor entries. Sparse covariance factorization is also discussed in [23] which focuses on stationary settings where the field sources/targets are immobile, while linear data models are considered and are not appropriate for tracking. Here the framework in [23] is generalized in *nonlinear*, highly *dynamic* and time-varying settings where sensors acquire information about multiple *moving* targets.

2. PROBLEM FORMULATION

Consider an ad-hoc multi-sensor network having m sensors. Every sensor can communicate with its single-hop neighboring sensors which are within its range. The single-hop neighborhood for sensor j will be denoted by $\mathcal{N}_j$, while the SN is modeled as an undirected graph with symmetric inter-sensor links. The connectivity information of the SN is summarized by the $m \times m$ adjacency matrix $\mathbf{E}$. Sensors monitor a field on which a time-varying and unknown number of moving targets is present. The targets are observed via measurements $x_j(t)$ acquired at sensor j and time $t = 0, 1, \ldots$ The targets are moving at different locations in the field affecting different parts of the SN. A general setting is considered where new targets are sensed at a given time, while other targets maybe becoming inactive.

The *scalar* measurement $x_j(t)$ adheres to the following model

$$x_j(t) = \sum_{\rho=1}^{R} a_\rho(t) d_{j,\rho}^{-2}(t) + w_j(t), \; j = 1, \ldots, m \qquad (1)$$

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where $a_\rho(t)$ denotes the intensity of a signal *emitted* by the ρth target, while $d_{j,\rho}(t)$ is the distance between the ρth target and sensor j at time t. R indicates the total number of different targets that move through the field over the lifetime of the SN, while $w_j(t)$ is zero-mean temporally white sensing noise with variance equal to σ_w^2. Note that (1) is formulated assuming that the targets act as transmitters, while the signals emitted from different targets propagate via free-space and are superimposed in the way described in (1) (see e.g., [8, Ch. 2]). Each of the $a_\rho(t)$ signals emitted by a moving target can be the result of, e.g., a radar signal impinging on the ρ target surface and then bouncing back. Thus, $a_\rho(t)$ could be viewed as the signal resulting after the radar signal has bounced back from target ρ surface and assuming that each sensor will receive one reflection of the bounced radar signal. It is also assumed that among these summands in (1) only one has strong amplitude whereas the rest are negligible. This pertains to a setting where only one target, say the ρth target, is close to sensor j whereas the rest are sufficiently far thus their impact is very small. This holds true when targets are well separated in space, and is a more 'relaxed' version of the common assumption that sensor measurements in multi-target tracking contain information about just *one* target [7,9,12,18,19,26]. The intensity $a_\rho(t)$ will be nonzero only for the interval for which a target is sensed by the sensors, otherwise will be zero.

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 of sensor j, while $\mathbf{p}_\rho(t) := [p_{\rho,x}(t), p_{\rho,y}(t)]^T \in \mathbb{R}^{2\times 1}$ denotes the unknown ρth target position in a 2-D plane. Each target, say the ρth is characterized by a 4×1 state vector $\mathbf{s}_\rho(t)$ that contains at a given time t its location $\mathbf{p}_\rho(t)$ and the velocity $\mathbf{v}_\rho(t) := [v_{\rho,x}(t), v_{\rho,y}(t)]^T$, i.e., $\mathbf{s}_\rho(t) := [\mathbf{p}_\rho^T(t), \mathbf{v}_\rho^T(t)]^T$. The target states evolve according to the following Markov model:

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

where $\mathbf{A}$ is the 4×4 transition matrix, while $\mathbf{u}_\rho(t)$ denotes zero-mean white Gaussian noise with covariance $\mathbf{\Sigma}_u$. Matrices $\mathbf{A}$ and $\mathbf{\Sigma}_u$ are given as (e.g., see [2])

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & \Delta T & 0 \\ 0 & 1 & 0 & \Delta T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \mathbf{\Sigma}_u = \sigma_u^2 \begin{bmatrix} \frac{(\delta T)^3}{3} \cdot \mathbf{I}_2 & \frac{(\delta T)^2}{2} \cdot \mathbf{I}_2 \\ \frac{(\delta T)^2}{2} \cdot \mathbf{I}_2 & \delta T \cdot \mathbf{I}_2 \end{bmatrix}$$

where δT is the sampling period, and σ_u^2 is a nonnegative constant controlling the variance of the noise entries in $\mathbf{u}_\rho(t)$, while $\mathbf{I}_2$ denotes the 2×2 identity matrix.

Stacking all sensor measurements in (1) on an $m \times 1$ vector we obtain the measurement model

$$\mathbf{x}_t = \mathbf{D}_t \mathbf{a}_t + \mathbf{w}_t, \text{ where } \mathbf{a}_t := [a_1(t)\ a_2(t) \ldots a_R(t)]^T, \tag{3}$$

while $\mathbf{D}_t$ is a $m \times R$ matrix with entries $\mathbf{D}_t(j,\rho) = d_{j,\rho}^{-2}(t)$ with $j = 1, \ldots, m$ and $\rho = 1, \ldots, R$. The noise $\mathbf{w}_t$ has covariance $\mathbf{\Sigma}_w = \sigma_w^2 \mathbf{I}_m$. Vector $\mathbf{x}_t$ is used for notational purposes, and is not actually stored in the system. Given that the entries of $\mathbf{a}_t$ are uncorrelated, it follows that the data covariance matrix is

$$\mathbf{\Sigma}_{x,t} = \mathbf{D}_t \mathbf{\Sigma}_a \mathbf{D}_t^T + \sigma_w^2 \mathbf{I}_m = \bar{\mathbf{D}}_t \bar{\mathbf{D}}_t^T + \sigma_w^2 \mathbf{I}_m, \tag{4}$$

where $\mathbf{\Sigma}_a$ is the diagonal covariance matrix of $\mathbf{a}_t$, while $\bar{\mathbf{D}}_t := \mathbf{D}_t \mathbf{\Sigma}_a^{1/2}$. Among the R entries in $\mathbf{a}_t$, there will be $r(t)$ nonzero entries corresponding to the active targets moving at the sensed field at t. Here once a target becomes inactive (i.e. $b_\rho(t) = 0$) it remains inactive.

The ρth column of $\mathbf{D}_t$ contains the distances of all sensors from target ρ at time t. For sensors close to target ρth, the corresponding distances, $d_{j,\rho}(t)$, will be relatively small, resulting relatively large entries $\mathbf{D}_t(j,\rho) = d_{j,\rho}^{-2}(t)$, compared to sensors that are further away. Since targets at a given instant t are very localized and close to a small percentage of sensors, many entries of any column, say the ρth, in $\mathbf{D}_t$ are expected to be close to zero giving rise to an approximately sparse matrix $\mathbf{D}_t$ (different from the stationary setting in [23]).

It is of interest to locate where the strong-amplitude and small-amplitude entries are located in the ρth column $\mathbf{D}_{t,\rho:}$ via which we can identify which sensors are close and acquire informative observations about a specific target, say the ρth. A spatio-temporal data association framework will be designed here that allows sensors to collaborate and determine which subsets of sensors acquire informative measurements about the $r(t)$ active targets at t. Sparsity-regularization techniques to estimate $\mathbf{D}_t$ and decompose it into sparse factors will be employed. The sensor-target association framework proposed here will then be integrated with particle filtering techniques to track accurately the targets' position.

3. SPATIO-TEMPORAL TARGET-TO-SENSOR DATA ASSOCIATION

The sparse sensor data covariance $\mathbf{\Sigma}_{x,t}$ is time-varying due to the changing number of targets and their movements, while in practical situations the ensemble covariance is not available. To this end the covariance entries will be estimated using exponential weighing

$$\hat{\mathbf{\Sigma}}_{x,t} = (1-\gamma)(1-\gamma^{t+1})^{-1} \textstyle\sum_{\tau=0}^{t} \gamma^{t-\tau} (\mathbf{x}_\tau - \bar{\mathbf{x}}_t)(\mathbf{x}_\tau - \bar{\mathbf{x}}_t)^T, \tag{5}$$

where $\gamma \in (0,1)$ denotes a forgetting factor and

$$\bar{\mathbf{x}}_t = (1-\gamma)(1-\gamma^{t+1})^{-1} \textstyle\sum_{\tau=0}^{t} \gamma^{t-\tau} x_\tau, \tag{6}$$

corresponds to an adaptive estimate for the data ensemble mean which is also time-varying. The scaling $(1-\gamma)(1-\gamma^{t+1})^{-1}$ in (5) and (6) is introduced to ensure that the time-varying covariance and mean estimates $\hat{\mathbf{\Sigma}}_{x,t}$ and $\bar{\mathbf{x}}_t$ will be unbiased estimates of the ensemble quantities $\mathbf{\Sigma}_{x,t}$ and $\mathbb{E}[\mathbf{x}_t]$ respectively, in a stationary setting. In order to adhere to the single-hop connectivity constraints summarized in the adjacency matrix $\mathbf{E}$, each sensor j is responsible for evaluating the 'single-hop' covariance entries $\hat{\mathbf{\Sigma}}_{x,t}(j,j')$ where $j' \in \mathcal{N}_j$.

3.1. Sparsity-Based Covariance Decomposition

A standard least-squares based matrix factorization scheme would minimize the Frobenius norm-based cost $\|\hat{\mathbf{\Sigma}}_{x,t} - \mathbf{M}_t\mathbf{M}_t^T - \sigma^2 \mathbf{I}_{m\times m}\|_F^2$ with respect to (wrt) the factor estimates in $\mathbf{M}_t \in \mathbb{R}^{m\times r}$. However, such a formulation does not account for the nearly sparse structure of $\bar{\mathbf{D}}_t$. In fact it assumes that the number r of factors (sensed targets) is available, while all covariance entries are available. The need for a framework that accounts for sparsity, unknown number of targets and single-hop connectivity is apparent. To this end, the following framework is put forth

$$\left(\hat{\mathbf{M}}_t, \{\hat{\sigma}_j\}_{j=1}^m\right) := \arg\min_{\mathbf{M}_t, \{\sigma_j\}_{j=1}^m} \|\mathbf{E} \odot \left(\hat{\mathbf{\Sigma}}_{x,t} - \mathbf{M}_t\mathbf{M}_t^T \right. \tag{7}$$

$$\left. - \mathrm{diag}(\sigma_{1,t}^2, \ldots, \sigma_{m,t}^2)\right)\|_F^2 + \sum_{\ell=1}^{L} \left(\lambda_\rho \|\mathbf{M}_{t,:\ell}\|_1 + \phi \|\mathbf{M}_{t,:\ell}\|_2\right),$$

where $\odot$ denotes the Hadamard operator (entry-wise matrix product), σ_j^2 is the local noise variance estimate at sensor j, while L is an upper bound for the number of active sensed targets $r(t)$ ($L \geq r(t)$) and $\mathbf{M}_{t,:\ell}$ denotes the ℓth column of $\mathbf{M}_t$. Although the sensing noise variance σ_w^2 is common across all sensors we introduce different noise variance estimates $\sigma_{j,t}^2$ to facilitate the development of a decentralized iterative minimization technique for (7). $\mathbf{M}_t \in \mathbb{R}^{m \times L}$ contains L columns that will estimate the sparse columns of $\bar{\mathbf{D}}_t$.

Sensor j will be updating the jth row in $\mathbf{M}_t$, namely $\mathbf{M}_{t,j:}$ for $j = 1, \ldots, m$. The adjacency matrix $\mathbf{E}$ in (7) along with the Hadamard operator allow only the available single-hop covariance entries to be used in the minimization formulation. The first term in (7) accounts for the structure in (4). The second term (norm-one) in (7) is well known (see e.g., [28]) to induce sparsity in the columns of $\mathbf{M}_t$ to account for the approximately sparse structure of $\bar{\mathbf{D}}_t$, while λ_ρ denotes the nonnegative sparsity-controlling coefficient used to induce zeros in factor $\hat{\mathbf{M}}_{t,:\rho}$. The third term in (7), where $\phi \geq 0$, promotes group sparsity among columns, see e.g., [29], and adjusts the number of nonzero columns of $\hat{\mathbf{M}}_t$ to accurately represent $\hat{\mathbf{\Sigma}}_{x,t}$.

3.2. Distributed Implementation

An iterative algorithm is proposed here to minimize the cost in (7) derived using coordinate descent [3,25]. The cost in (7) is minimized recursively wrt an entry of $\mathbf{M}_t$ or $\text{diag}(\sigma_1^2, \ldots, \sigma_m^2)$, while keeping the remaining entries fixed. During one coordinate descent cycle all the entries of $\mathbf{M}_t$ and $\text{diag}(\sigma_{1,t}^2, \ldots, \sigma_{m,t}^2)$ are updated. Sensor j is updating the entries $\{\mathbf{M}_t(j,\ell)\}_{\ell=1}^L$ and $\sigma_{j,t}^2$. Given the most recent updates $\hat{\mathbf{M}}_t^{k-1}$ and $\{\sigma_{j,t,k-1}^2\}$ at the end of coordinate cycle $k-1$, updates $\hat{\mathbf{M}}_t^k(j,\ell)$ at sensor j can be formed by differentiating (7) wrt $\mathbf{M}_t(j,\ell)$ while fixing the rest of the minimization variables to their most up-to-date values from cycle $k-1$. It turns out that during coordinate cycle k, the update $\hat{\mathbf{M}}_t^k(j,\ell)$ can be obtained as the value that gets the minimum possible cost in (7) (while fixing the rest of the variables) among the candidate values: i) $z = 0$; ii) the real positive roots of the third-degree polynomial

$$4z^3 + 4\left[\sum_{i \in \mathcal{N}_j} [\hat{\mathbf{M}}_t^{k-1}(i,\ell)]^2 - \zeta_{t,\Sigma}^k(j,j,\ell) + 0.5\phi\right] z \\ - \left[4 \sum_{i \in \mathcal{N}_j} \zeta_{t,\Sigma}^k(j,\mu,\ell)\hat{\mathbf{M}}_t^{k-1}(i,\ell)\right] + \lambda_\ell = 0 \tag{8}$$

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

$$4z^3 + 4\left[\sum_{i \in \mathcal{N}_j} [\hat{\mathbf{M}}_t^{k-1}(\mu,\ell)]^2 - \zeta_{t,\Sigma}^k(j,j,\ell) + 0.5\phi\right] z \\ - \left[4 \sum_{i \in \mathcal{N}_j} \zeta_{t,\Sigma}^k(j,i,\ell)\hat{\mathbf{M}}_t^{k-1}(i,\ell)\right] - \lambda_\ell = 0 \tag{9}$$

where

$$\zeta_{t,\Sigma}^k(j,i,\ell) := \hat{\mathbf{\Sigma}}_{x,t}(j,i) - \delta_{j,i}\hat{\sigma}_{j,t,k-1}^2 \\ - \sum_{\ell'=1, \ell' \neq \ell}^{L} \hat{\mathbf{M}}_t^{k-1}(j,\ell')\hat{\mathbf{M}}_t^{k-1}(i,\ell') \tag{10}$$

while $\delta_{j,i}$ denotes the Kronecker delta, i.e., $\delta_{j,i} = 1$ if $j = i$, and $\delta_{j,i} = 0$ if $j \neq i$.

Further, the noise variance estimates across sensors can be updated during cycle k at time instant t as

$$\hat{\sigma}_{j,t,k}^2 = \hat{\mathbf{\Sigma}}_{x,t}(j,j) - \hat{\mathbf{M}}_{t,j:}^k(\hat{\mathbf{M}}_{t,j:}^k)^T, \;\; j = 1, \ldots, m. \tag{11}$$

The roots of (8) and (9) can be found via companion matrices [10]. Sensor j evaluates the coefficients of the polynomials in (8) and (9) by communicating only with its neighbors in $\mathcal{N}_j$. In detail, sensor j receives $\{\hat{\mathbf{M}}_t^{k-1}(i,1), \ldots, \hat{\mathbf{M}}_t^{k-1}(i,L)\}$ and measurements $\{x_i(t)\}$ from sensors $i \in \mathcal{N}_j$ to form $\hat{\mathbf{\Sigma}}_{x,t}(j,i)$ and $\zeta_{t,\Sigma}^k(j,i,\ell)$. Similarly, it sends to its neighbors the L scalar updates for the jth row of $\mathbf{M}_t$, namely $\{\hat{\mathbf{M}}_t^{k-1}(j,1), \ldots, \hat{\mathbf{M}}_t^{k-1}(j,L)\}$ and its current measurement $x_j(t)$. Further, each sensor j can update the noise variance estimates $\hat{\sigma}_{j,t,k}^2$ using only locally available information as can be seen in (11). To facilitate a real-time implementation a small fixed number, say κ, of coordinate cycles is applied per time t. Note that the proposed scheme also involves constant updating of the single-hop covariance entries $\hat{\mathbf{\Sigma}}_{x,t}(j,i)$ needed in $\zeta_{t,\Sigma}^k(j,i,\ell)$ to account for the constantly changing statistical properties of the sensed field. It can be shown that as $k \to \infty$ the updates $\{\hat{\mathbf{M}}_t^{k-1}$ converge at least to a stationary point of (7). Further, the parameters $\{\lambda_\ell\}_{\ell=1}^L$ can be set using the strategy proposed in [23]. To end the iterative process each sensor j proceeds to evaluate the Euclidean norm of the difference between two consecutive estimates, namely $\|\hat{\mathbf{M}}_{t,j:}^{k-1} - \hat{\mathbf{M}}_{t,j:}^k\|_2$, found during iteration steps k and $k-1$. Once the maximum norm $\|\hat{\mathbf{M}}_{t,j:}^{k-1} - \hat{\mathbf{M}}_{t,j:}^k\|_2$ is less than a threshold ϵ (in our tests is set as $5 \cdot 10^{-3}$), then the updating process stops.

Once the nonzero sparse factors $\{\hat{\mathbf{M}}_{t,:\ell}\}_{\ell=1}^{\hat{r}(t)}$ are estimated, where $\hat{r}(t) < L$ corresponds to the number of nonzero columns of $\hat{\mathbf{M}}_t := \hat{\mathbf{M}}_t^\kappa$ at t, their support (nonzero entries) can be used to identify the sensors that sense a specific target at time instant t. In that way sensor subsets $\mathcal{T}_{\ell_t,t}$ for $\ell_t = 1, \ldots, \hat{r}(t)$ can be identified and used to track the different targets.

4. JOINT ASSOCIATION AND TRACKING

During a start-up stage each sensor acquires T_s measurements, namely $\{x_j(\tau)\}_{\tau=-(T_s-1)}^0$. It is assumed that the sampling rate is fast enough such that the present targets, say $r(0)$ in number, can be assumed essentially immobile. The T_s acquired data are then used by the distributed sensor-target association framework in Sec. 3 to initialize the sets of informative sensors $\{\mathcal{T}_{\rho_\ell^0,0}\}_{\ell=1}^{\hat{r}(0)}$ where each $\rho_\ell^0 \in \{1, \ldots, R\}$ for $\ell = 1, \ldots, \hat{r}(0)$, and $\hat{r}(0)$ is the estimated number of $r(0)$ sensed targets at time $t = 0$ (number of nonzero columns in $\hat{\mathbf{M}}_0$). One sensor in each set $\mathcal{T}_{\rho_\ell^0,0}$ is designated as a leading sensor $C_{\rho_\ell^0,0}$ which collects from all sensors $j \in \mathcal{T}_{\rho_\ell^0,0}$ their corresponding measurements $x_j(0)$ and their position $\mathbf{p}_j$ for $j \in \mathcal{T}_{\rho_\ell^0,0}$ and $\ell = 1, \ldots, \hat{r}(0)$. During initialization the leading sensor $C_{\rho_\ell^0,0}$ can be selected randomly among the sensors in $\mathcal{T}_{\rho_\ell^0,0}$. Then, for time $t > 0$ it will be described later on how the leading sensors are selected. Each leading sensor $C_{\rho_\ell^0,0}$, for $\ell = 1, \ldots, \hat{r}(0)$, then calculates the 'average' informative sensors' position as $\hat{\mathbf{p}}_{\rho_\ell^0}(0) = \sum_{j \in \mathcal{T}_{\rho_\ell^0,0}} \mathbf{p}_j$ for $\ell = 1, \ldots, \hat{r}(0)$. Each leading sensor $C_{\rho_\ell^0,0}$ uses the average location $\hat{\mathbf{p}}_{\rho_\ell^0}(0)$ to initialize the standard particle filter recursions [6] corresponding to models (1) and (2); and find a state estimate $\hat{\mathbf{s}}_{\rho_\ell^0}(0)$ for target ρ_ℓ^0 using the informative measurements $x_j(0)$, for $j \in \mathcal{T}_{\rho_\ell^0,0}$ and $\ell = 1, \ldots, \hat{r}(0)$.

Suppose that at time t each leading sensor $\{C_{\rho_\ell,t}\}$ has available state estimates $\hat{\mathbf{s}}_{\rho_\ell}(t)$ for $\ell = 1, \ldots, \hat{r}(t)$. From $\hat{\mathbf{s}}_{\rho_\ell}(t)$ the estimated target position $\hat{\mathbf{p}}_{\rho_\ell}(t)$ can be extracted and it is utilized to select a set of 'candidate' target-informative sensors, namely $\mathcal{J}_{\rho_\ell,t+1}$, for target ρ_ℓ. Specifically, the leading sensor $C_{\rho_\ell,t}$ transmits $\hat{\mathbf{s}}_{\rho_\ell}(t)$ to its single-hop neighbors, which will subsequently transmit to their own neighbors and the estimate propagates in time. A sensor j that receives $\hat{\mathbf{s}}_{\rho_\ell}(t)$ will forward this estimate only to those neighbors in

$j' \in \mathcal{N}_j$ that are located within a radius R_s from the estimated target location, i.e., $\|\mathbf{p}_{j'} - \hat{\mathbf{s}}_{\rho_\ell}(t)\|_2 \leq R_s$.

In each of the subsets $\mathcal{J}_{\rho_\ell,t+1}$ the targets-to-sensors association scheme in Sec. 3 is employed to determine the target-informative sensor groups $\mathcal{T}_{\rho_\ell,t+1} \subseteq \mathcal{J}_{\rho_\ell,t+1}$ for each of the targets ρ_ℓ at time instant $t+1$. The radius R_s through which $\mathcal{J}_{\rho_\ell,t+1}$ are constructed is up to our control, and the faster the target moves the larger R_s should be set to guarantee that all target-informative sensors are included in $\mathcal{J}_{\rho_\ell,t+1}$. Performing the target-to-sensor association algorithm in different sensor subsets $\mathcal{J}_{\rho_\ell,t+1}$ of the SN facilitates tracking the present targets, while it requires less computational and communication complexity than when applied in the whole SN.

The leading sensor $C_{\rho_\ell,t+1}$ is chosen as that sensor in $\mathcal{T}_{\rho_\ell,t+1}$, which is closest to the estimated position of the ρ_ℓth target, i.e., $C_{\rho_\ell,t+1} = \arg\min_{j \in \mathcal{T}_{\rho_\ell,t+1}} \|\mathbf{p}_j - \hat{\mathbf{p}}_{\rho_\ell}(t)\|_2$. The process of electing a new leading sensor can take place among the sensors in $\mathcal{T}_{\rho_\ell,t+1}$ that can determine their distance from $\hat{\mathbf{p}}_{\rho_\ell}(t)$ and find which sensor has the minimum in a distributed fashion, e.g., see [13]. The leading sensor $C_{\rho_\ell,t+1}$ then collects i) the corresponding Q state particles and weights $\{\mathbf{s}^i_{\rho_\ell,t}, w^i_{\rho_\ell,t}\}_{i=1}^Q$ from $C_{\rho_\ell,t}$; and ii) the sensors measurements $x_j(t+1)$ for $j \in \mathcal{T}_{\rho_\ell,t+1}$, namely the updated informative sensor subset for target ρ_ℓth at time instant $t+1$.

The leading sensor $C_{\rho_\ell,t+1}$ proceeds to draw Q new state particles and update their corresponding weights as in [6]. Then, $C_{\rho_\ell,t+1}$ forms the new state estimate $\hat{\mathbf{s}}_{\rho_\ell}(t+1) \approx E[\mathbf{s}_{\rho_\ell}(t+1)|\mathbf{x}_{\mathcal{T}_{\rho,0:t}}]$ using the PF updating recursions in [6] to find the estimated location for target ρ_ℓ at time instant t, namely $\hat{\mathbf{p}}_{\rho_\ell}(t+1)$. The leading sensor $C_{\rho_\ell,t+1}$ transmits $\hat{\mathbf{s}}_{\rho_\ell}(t+1)$ to its single-hop neighbors and the process described earlier is repeated.

5. NUMERICAL TESTS

Next, we test the tracking performance of our novel method in a setting where the number of targets can change in time. A number of $m = 120$ sensors are placed randomly in the region of $[0, 100] \times [0, 100]m^2$. The total number of targets is $R = 12$. The radius R_s for determining the candidate informative sensors subsets $\mathcal{J}_{\rho,t}$ is set equal to $R_s = 10$. The forgetting factor is set as $\gamma = 0.1$. The state noise variance is set as $\sigma_u^2 = 0.1$, while the measurement noise variance is set to $\sigma_w^2 = 0.1$ (amounts to a sensing SNR of 10dB).

The target configuration [see Fig. 1 (top)] is set as follows: Targets $\rho = 1, 2, 3$ start moving at positions $[35, 25]$, $[40, 45]$, $[20, 55]$ and follow the dynamics in (2). In detail, targets $\rho = 1, 3$ move at a speed of $2m/s$ across the x-axis, target $\rho = 2$ moves with a speed of $2m/s$ across the y-axis. Targets $\rho = 1, 2, 3$ move in the field for the time interval $[1, 15]$s and then are not sensed anymore. In the interval $[15, 17]$s no targets are present in the field. Then, targets $\rho = 4, 5$ start at positions $[23, 40]$, $[50, 75]$ and move according to same state model followed by the first three for the time interval $[17, 30]$s but with speeds $-1.3m/s$ and $-1.7m$ respectively across the x-axis. Again no targets are present during $[30, 32]$s. Then, targets $\rho = 6, 7$ appear at initial positions $[75, 35]$, $[10, 30]$ and start moving for the time interval $[32, 45]$s with a speed of $1.5m/s$ on the x-axis and $1.7m/s$ across the y-axis. Three new targets, namely $\rho = 8, 9, 10$, show up at positions $[40, 70]$, $[40, 10]$, $[60, 70]$ and move in the field for the time interval $[47, 60]$s with different speed $1.4, 1.2, 1.6m/s$ on both the y and x-axis. Finally, the last two targets $\rho = 11, 12$ start at positions $[85, 25]$ and $[48, 48]$ and move within the field for the time interval $[62, 72]$s. Target $\rho = 11$ moves with $-1.0m/s$ and $2.6m/s$ across x and y-axis, while target $\rho = 12$ with corresponding x-axis and y-axis speeds of $-0.7m/s$ and $-2.5m/s$, respectively.

Fig. 1 (top) depicts the true target trajectories (blue dashed curves), along with the estimated trajectories (light green curves) using our novel method. The blue stars correspond to the starting position of the targets and the red stars denote the ending position. Fig. 1 (bottom) depicts the average tracking root mean square error (RMSE) corresponding to the tracking of the different targets present in Fig. 1 (top). We compare our method with i) the standard particle filtering, where instead of performing data association a 48×1 augmented state vector that contains all targets' states is tracked; and ii) the unscented Kalman filter (UKF) tracking scheme (e.g., see [14]) combined with the targets-to-sensors association scheme in Sec. 3.

Note that at the time intervals $15, 30, 45, 60$s the average tracking RMSE is zero in Fig. 1 (bottom). It is initialized there because during these time intervals no targets are detected in the field and thus there is nothing to track and no corresponding tracking RMSE. However, when targets are present, clearly our method achieves better tracking performance compared to standard PF and the UKF based methods. Our approach achieves a smaller RMSE for the same number of particles ($Q = 100$) wrt standard PF since the former effectively associates targets with sensor measurements. UKF performs worse since it just estimates the posterior mean and covariance instead of tracking the posterior probability density function. The probability of incorrect sensor-to-target association is 0.08.

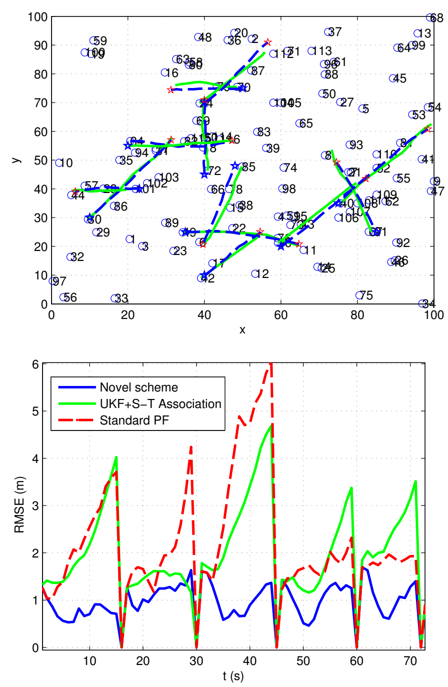

Fig. 1. (top) Tracking of multiple targets. (Bottom) Average tracking RMSE versus time.

6. CONCLUDING REMARKS

A novel method performing distributed sensor-target association and multi-target tracking was designed and tested in multi-sensor networks. Our approach is based on a novel blending of particle filtering and sparsity-aware matrix factorization techniques. The target-informative sensors are chosen online and their observations are used for tracking. Numerical tests show that the proposed tracking framework outperforms related approaches in tracking multiple targets.

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