TARGET TRACKING IN A TWO-TIERED HIERARCHICAL SENSOR NETWORK

Mahesh Vemula, Mónica F. Bugallo, Petar M.Djurić

Dept. of Electrical and Computer Engineering,
Stony Brook University, Stony Brook, NY, 11794-2350

ABSTRACT

An important application of sensor networks is target tracking and localization. To deal with sensor nodes with limited energy supply and communication bandwidth we propose energy-efficient hierarchical architectures for solving the target tracking problem. In these networks, sensors form clusters and transmit minimal quantized information about a sensed event to a specialized node, known as a cluster head. Cluster heads are equipped with capability of communicating over large distances with a fusion center or a base station. We consider two different hierarchical architectures : (a) the target dynamics are probabilistically estimated at the cluster heads and their statistics combined at the fusion center, and (b) the cluster heads perform simple compression rules on the quantized sensor data and the fusion center estimates the target dynamics using these severely compressed data. Sequential Monte Carlo algorithms for estimation of the target dynamics are used. Through computer simulations the performances of these two architectures are studied.

1. INTRODUCTION

Rapid advances in the manufacturing of tiny low cost and low power sensor devices are paving the way for pervasive sensing and ubiquitous computing. Being inexpensive and small in size these sensors are deployed in large number for purposes of monitoring ecosystems, or detecting faults and intrusions in both military and civilian scenarios. Other growing applications of wireless sensor networks include automotive telematics, smart bridges, and inventory tracking and management [1]. The constraints in computation power, battery power, and communication bandwidth of these sensors have generated numerous challenges towards the design of energy-efficient sensor networking architectures, protocols and algorithms for increased accuracy and improved system throughput.

A typical sensor network comprises of a large number of sensors, which perform tasks of sensing, local data processing and transmission of data to a central unit, known as a base station (BS) or a fusion center (FC). In flat network architectures, where all the sensors transmit the data to the FC either directly or route the data to the FC through intermediary sensor nodes, a considerable amount of sensor energy is dissipated in communication. In view of these drawbacks, hierarchical sensor network (HSN) architectures have been proposed [2, 3]. At the lowest level (tier 0), sensors form a cluster and a selected node receives the sensed data transmitted from the sensors in the cluster. The selected node is known as leader node (LN) or cluster head (CH). The CHs may form a second level (tier 1) of hierarchy. In a two-tiered hierarchical architecture, communication proceeds among (a) sensor nodes and CHs and (b) CHs and FC, thereby adverting the need for direct communication between sensors and FC. As a result, with CHs relatively closer to the sensors than the FC, the energy consumption by each sensor for data transmission is considerably reduced. While sensors may have multiple CHs, here we consider the situation where a sensor has only one CH.

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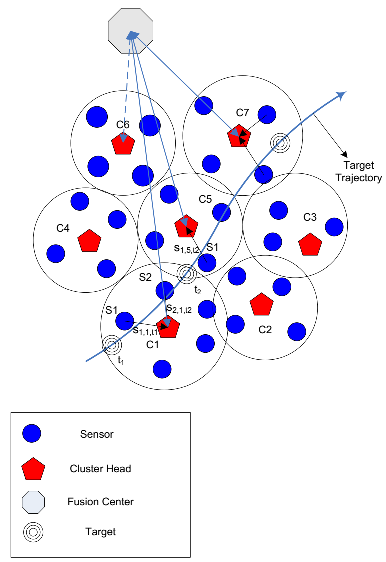

Fig. 1. Hierarchical Sensor Network

In this paper, we address target tracking in two-tiered hierarchical sensor networks. The CHs are assumed capable of communicating directly with the FC [4]. The sensors use a simple quantization scheme that results in transmission of a '1' when the target is in their vicinity and a '0' otherwise. We consider the following two HSN architectures.

- When CHs have medium to high computational resources, target tracking is performed at the CH using the quantized data. We term this architecture as HSN-Type I.
- When CHs have low computational resources, the CHs employ simple compression rules and transmit this compressed data to the FC. We term this architecture as HSN-Type II. In this paper, the compression rule accounts for the transmission of a single number that represents the number of sensors reporting the event of interest in their neighborhood.

Fig. 1 shows an example of a HSN. We consider a cluster as active, when any of its sensors report events of activity in their neighborhood. Clusters are inactive if there are no sensors that sense any activity in their neighborhood. In the example, at time instant t_1 C1 is an active cluster while CHs C2 and C4 are inactive. At time instant t_1, when the target is within the vicinity of sensor S1, the sensor transmits a 1 to the CH C1, which processes the data and transmits them to the FC. At time instant t_2, sensors S2 and S1 of CHs C1 and C5 respectively, report the presence of the target. In a HSN-Type I, the CH C1 and C5 independently estimate the target dynamics and the FC combines these estimates, while in HSN-Type II, the CHs transmit the number of 1s, that each of them received from its sensors. We propose sequential Monte Carlo (SMC) algorithms for target tracking and data fusion in HSNs-Type I and Type II.

The organization of the paper is as follows: in Section 2, the main components of the sensor network, the sensor, the CHs, and the FC are defined. In Section 3, a detailed description of SMC methods for target tracking in these networks is provided and in Section 4, simulation results are presented. Finally we conclude the paper in Section 5.

2. SYSTEM OVERVIEW

2.1. Sensor Model

Following the work in [5], we model the strength of the signal emitted by target and received at the sensor as

$$y_{n,c,t} \quad = \quad \min\left(\mathbf{\Psi}_0, \frac{\mathbf{\Psi}_0 d_0^\alpha}{|\mathbf{r}_{n,c} - \mathbf{d}_t|^\alpha}\right) + v_{n,c,t} \qquad (1)$$

where $\mathbf{\Psi}_0$ is the signal strength within a known reference distance d_0, $\mathbf{r}_{n,c} \in \mathbb{R}^2$ is the position of the n-th sensor in the c-th cluster, $\mathbf{d}_t \in \mathbb{R}^2$ denotes the location of the target at time t, $|\cdot|$ denotes norm (length) of a vector, α is the attenuation parameter and $v_{n,c,t} \sim N(\mu_v, \sigma_v^2)$ is a noise process with Gaussian probability density function whose statistics are assumed known. In equation (1), the unknown quantities are $\mathbf{\Psi}_0$ and $\mathbf{d}_t$. If the observed energy level $y_{n,c,t}$, exceeds a threshold γ, the sensor transmits a binary 0, otherwise it transmits a 1 [6]. Mathematically this processing is modeled as

$$s_{n,c,t} = \begin{cases} 1 & \Leftarrow \quad y_{n,c,t} \geq \gamma \\ 0 & \Leftarrow \quad y_{n,c,t} < \gamma. \end{cases} \qquad (2)$$

2.2. Cluster Head Model

In a HSN-Type I, the active CHs using the binary data, $s_{n,c,t} \in \{1, 0\}$, from the sensors, estimate the target dynamics and transmit these statistics to the FC. In a HSN-Type II, the CH transmits the number of active sensors in its cluster to the FC. The transmitted signal to the FC is modeled as

$$z_{c,t} = \sum_{n=1}^{N_c} s_{n,c,t} \qquad (3)$$

where N_c is the number of sensors in the c-th cluster. The total number of clusters in the proposed networks is C.

2.3. Fusion Center Model

Reiterating, the role of the FC in HSNs-Type I, is to combine the estimates of the CHs when multiple clusters are active and to provide the initialization parameters of the SMC filter implemented on the active clusters. In these networks the FC does not require any location information of the sensors. In HSNs-Type II, the FC collects the severely quantized sensor data from the CHs and estimates the target statistics. In this type of network the FC needs to know the location of the sensors and the indices of the CHs to which they belong.

3. SMC ALGORITHMS FOR TARGET TRACKING

SMC methods, also known as particle filtering methods, are well suited for non-linear filtering problems where the posterior distribution of the system state vector $\mathbf{x}_t$ is approximated by a random measure which consists of a set of weighted samples [7]. These samples are also known as particles. At a given time instant, the particles are propagated using a proposal density and the weights are recursively updated. In a SMC framework, the target tracking problem is formulated as a non-linear filtering problem, with the target's dynamic parameters as the system state vector. The target movement model here plays the role of the state transition equation. Denoting $\mathbf{x}_t = [\dot{x}_{1,t}, \dot{x}_{2,t}, x_{1,t}, x_{1,t}, \Psi_t]^\top$, and defining $\mathbf{l}_t = [x_{1,t},\ x_{2,t},\ \Psi_t]^\top$ as the vector containing the position of the target and the reference signal strength and $\boldsymbol{v}_t = [\dot{x}_{1,t},\ \dot{x}_{2,t}]^\top$ as the velocity vector, we model the state transition equations as

$$\begin{aligned} \boldsymbol{v}_t &= \boldsymbol{v}_{t-1} + \mathbf{F}_{t-1}\mathbf{u}_t \\ \mathbf{l}_t &= \mathbf{G}_{t-1}^1 \boldsymbol{v}_{t-1} + \mathbf{G}_{t-1}^2 \mathbf{l}_{t-1} + \mathbf{G}_{t-1}^3 \boldsymbol{v}_t \end{aligned} \qquad (4)$$

where

$$\mathbf{F}_t = \begin{bmatrix} Ts & 0 \\ 0 & Ts \end{bmatrix}, \qquad \mathbf{G}_{t-1}^1 = \begin{bmatrix} \frac{Ts}{2} & 0 \\ 0 & \frac{Ts}{2} \\ 0 & 0 \end{bmatrix}$$

$$\mathbf{G}_{t-1}^2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \qquad \mathbf{G}_{t-1}^3 = \begin{bmatrix} \frac{Ts}{2} & 0 \\ 0 & \frac{Ts}{2} \\ 0 & 0 \end{bmatrix}$$

and $\mathbf{u}_t$ is a Gaussian noise process with zero mean and covariance matrix $\mathbf{C}_u$. The observation equation (1), can be rewritten as

$$y_{n,c,t} = h(x_{1:2,t}, \mathbf{r}_{n,c}) + v_{n,t}^c \qquad (5)$$

where $h(x_{1:2,t}, \mathbf{r}_{n,c}) = \min\left(\mathbf{\Psi}_0, \frac{\mathbf{\Psi}_0 d_0^\alpha}{|\mathbf{r}_{n,c} - \mathbf{d}_t|^\alpha}\right)$. Within this framework, the objectives are

- Estimation of the posterior density $p(\mathbf{x}_t | s_{1,c,1:t}, \cdots, s_{N_c,c,1:t})$ by active CH c and fusion of the statistics of these densities of multiple CHs by the FC in a HSN-Type I.
- Estimation of the posterior density $p(\mathbf{x}_t | \mathbf{z}_{1,1:t}, \cdots, \mathbf{z}_{C,1:t})$ by the FC in a HSN-Type II.

3.1. CH Particle Filter Implementation in HSN-Type I

The following are the steps of the implementation of a particle filter at a CH in HSN-Type I networks.

1. Initialization: $\mathbf{x}_{t'}^{(m)} \sim \mathcal{N}(\boldsymbol{\mu}_{t'}, \boldsymbol{\Xi}_{t'})$ where $\{\boldsymbol{\mu}_{t'}, \boldsymbol{\Xi}_{t'}\}$ are provided by the FC and $m \in \{1 \cdots M\}$ denotes the particle index with M as the total number of particles.
2. Particle generation : The particles of the new state $\mathbf{x}_t^{(m)}$ are generated as

$$\begin{aligned} \dot{x}_{(1,2),c,t}^{(m)} &\sim \mathcal{N}(\dot{x}_{(1,2),c,t-1}^{(m)}, T_s^2 \sigma_{(1,2),u}^2) \\ x_{(1,2),c,t}^{(m)} &= x_{(1,2),c,t-1}^{(m)} + \frac{T_s}{2}\left(\dot{x}_{(1,2),c,t}^{(m)} + \dot{x}_{(1,2),c,t-1}^{(m)}\right) \\ \Psi_{c,t}^{(m)} &\sim \mathcal{N}(\mu_{\Psi_{c,t-1}}, \sigma_{\Psi_{c,t-1}}^2). \end{aligned} \qquad (6)$$

3. Weight update and normalization:

$$\begin{aligned} \tilde{w}_{c,t}^{(m)} &\propto w_{c,t-1}^{(m)} \prod_{n=1}^{N_c} p(s_{n,c,t}|\mathbf{x}_{0:t}^{(m)}) \qquad (7) \\ w_{c,t}^{(m)} &= \frac{\tilde{w}_{c,t}^{(m)}}{\sum \tilde{w}_{c,t}^{(m)}} \end{aligned}$$

4. Estimation of transmitted kernel parameters:

$$\begin{aligned} \hat{\boldsymbol{\mu}}_{c,t} &= \sum_{m=1}^{M} w_{c,t}^{(m)} \mathbf{x}_{c,t}^{(m)} \\ \hat{\boldsymbol{\Sigma}}_{c,t} &= \sum_{m=1}^{M} w_t^{(m)} (\mathbf{x}_{c,t}^{(m)} - \hat{\boldsymbol{\mu}}_{c,t})(\mathbf{x}_{c,t}^{(m)} - \hat{\boldsymbol{\mu}}_{c,t})^\top. \end{aligned}$$

The likelihood in (8) is evaluated using the following expressions:

$$\begin{aligned} & p(s_{n,c,t}=1|\mathbf{x}_{0:t}^{(m)}) = 1 - p(s_{n,c,t}=0|\mathbf{x}_{0:t}^{(m)}) \\ &= \int_{\gamma}^{\infty} p(y_{n,c,t}|\mathbf{x}_{0:t}^{(m)}) dy_{n,c,t} = Q\left(\frac{\gamma - h(x_{1:2,t}, \mathbf{r}_{n,c}) - \mu_v}{\sigma_v}\right). \end{aligned} \qquad (8)$$

The FC collects the transmitted kernel parameters from the CHs and utilizes them in fusion of the posterior densities of multiple active CHs as described in the next subsection.

3.2. Fusion Center in HSN-Type I

We denote $\mathbf{s}_{c,t} = \{s_{1,c,t}, \cdots, s_{N_c,c,t}\}$ as the set of sensor measurements in cluster c at time instant t, $\mathbf{s}_{c,1:t} = \{s_{1,c,1:t}, \cdots, s_{N_c,c,1:t}\}$ as the set of sensor measurements from time instant 1 to t and $\mathbf{s}_{1:C_a,t} = \{\mathbf{s}_{1,1:t}, \cdots, \mathbf{s}_{C_a,1:t}\}$ as the set of all sensor measurements in C_a clusters from time instant 1 to t. Let us consider measurements evolving from sensors of two different clusters ($C_a = 2$). The joint posterior density of the target dynamics can then be derived as

$$\begin{aligned} & p(\mathbf{x}_{0:t}|\mathbf{s}_{1:2,1:t}) = p(\mathbf{x}_{0:t}|\mathbf{s}_{1:2,t}, \mathbf{s}_{1:2,1:t-1}) \\ & \propto p(\mathbf{s}_{1,t}, \mathbf{s}_{2,t}|\mathbf{x}_t, \mathbf{x}_{0:t-1}, \mathbf{s}_{1:2,1:t-1}) p(\mathbf{x}_t|\mathbf{x}_{0:t-1}, \mathbf{s}_{1:2,1:t-1}) \\ & \qquad \times p(\mathbf{x}_{0:t-1}|\mathbf{s}_{1:2,1:t-1}) \\ & \propto \frac{p(\mathbf{x}_t|\mathbf{s}_{2,1:t})}{p(\mathbf{x}_t|\mathbf{s}_{1,1:t-1})} \frac{p(\mathbf{x}_t|\mathbf{s}_{2,1:t})}{p(\mathbf{x}_t|\mathbf{s}_{2,1:t-1})} p(\mathbf{x}_t|\mathbf{x}_{t-1}) p(\mathbf{x}_{0:t-1}|\mathbf{s}_{1:2,1:t-1}). \end{aligned} \qquad (9)$$

assuming independence among the sensor measurements $\{\mathbf{s}_{1,t}, \mathbf{s}_{2,t}\}$ conditioned on $\mathbf{x}_t$ [8]. Generalizing equation (9) for C_a number of active clusters, we have

$$\begin{aligned} p(\mathbf{x}_{0:t} \mid \mathbf{s}_{1:C_a,1:t}) &\propto \prod_{c=1}^{C_a} \frac{p(\mathbf{x}_t \mid \mathbf{s}_{c,1:t})}{p(\mathbf{x}_t \mid \mathbf{s}_{c,1:t-1})} \times \\ & p(\mathbf{x}_t \mid \mathbf{x}_{t-1}) p(\mathbf{x}_{0:t-1} \mid \mathbf{s}_{1:C_a,1:t-1}) \end{aligned} \qquad (10)$$

which is the optimal recursive fusion equation. The CHs approximate the sampled based representations of the distributions $p(\mathbf{x}_t \mid \mathbf{s}_{c,1:t-1})$ and $p(\mathbf{x}_t \mid \mathbf{s}_{c,1:t})$ as Gaussians, i.e., $p(\mathbf{x}_t \mid \mathbf{s}_{c,1:t-1}) \simeq \mathcal{N}(\tilde{\boldsymbol{\mu}}_{c,t}, \tilde{\boldsymbol{\Sigma}}_{c,t})$ and $p(\mathbf{x}_t \mid \mathbf{s}_{c,1:t}) \simeq \mathcal{N}(\hat{\boldsymbol{\mu}}_{c,t}, \hat{\boldsymbol{\Sigma}}_{c,t})$. Therefore, from (10) we have

$$\begin{aligned} p(\mathbf{x}_t \mid \mathbf{s}_{1:C_a,1:t}) &\propto \prod_{c=1}^{C_a} \frac{\mathcal{N}(\hat{\boldsymbol{\mu}}_{c,t}, \hat{\boldsymbol{\Sigma}}_{c,t})}{\mathcal{N}(\tilde{\boldsymbol{\mu}}_{c,t}, \tilde{\boldsymbol{\Sigma}}_{c,t})} \\ & \times\ p(\mathbf{x}_t \mid \mathbf{x}_{t-1})\, p(\mathbf{x}_{0:t-1} \mid \mathbf{s}_{1:C,1:t-1}) \\ & \propto \frac{\mathcal{N}(\hat{\boldsymbol{\mu}}_t, \hat{\boldsymbol{\Sigma}}_t)}{\mathcal{N}(\tilde{\boldsymbol{\mu}}_t, \tilde{\boldsymbol{\Sigma}}_t)}\, p(\mathbf{x}_t \mid \mathbf{x}_{t-1})\, p(\mathbf{x}_{0:t-1}|\mathbf{s}_{1:C_a,1:t-1}) \end{aligned}$$

where

$$\begin{aligned} \hat{\boldsymbol{\Sigma}}_t^{-1} &= \hat{\boldsymbol{\Sigma}}_{1,t}^{-1} + \hat{\boldsymbol{\Sigma}}_{2,t}^{-1} + \cdots + \hat{\boldsymbol{\Sigma}}_{C_a,t}^{-1} \\ \hat{\boldsymbol{\mu}}_t &= \hat{\boldsymbol{\Sigma}}_t \left(\hat{\boldsymbol{\Sigma}}_{1,t}^{-1}\hat{\boldsymbol{\mu}}_{1,t} + \hat{\boldsymbol{\Sigma}}_{2,t}^{-1}\hat{\boldsymbol{\mu}}_{2,t} + \cdots + \hat{\boldsymbol{\Sigma}}_{C_a,t}^{-1}\hat{\boldsymbol{\mu}}_{C_a,t}\right) \\ \tilde{\boldsymbol{\Sigma}}_t^{-1} &= \tilde{\boldsymbol{\Sigma}}_{1,t}^{-1} + \tilde{\boldsymbol{\Sigma}}_{2,t}^{-1} + \cdots + \tilde{\boldsymbol{\Sigma}}_{C_a,t}^{-1} \\ \tilde{\boldsymbol{\mu}}_t &= \tilde{\boldsymbol{\Sigma}}_t \left(\tilde{\boldsymbol{\Sigma}}_{1,t}^{-1}\tilde{\boldsymbol{\mu}}_{1,t} + \tilde{\boldsymbol{\Sigma}}_{2,t}^{-1}\tilde{\boldsymbol{\mu}}_{2,t} + \cdots + \tilde{\boldsymbol{\Sigma}}_{C_a,t}^{-1}\tilde{\boldsymbol{\mu}}_{C_a,t}\right) \end{aligned} \qquad (11)$$

A particle filter based implementation of the fusion equation (10), is similar to the CH particle filter implementation outlined in subsection 3.1 except for the weight calculation, which is performed as $\tilde{w}_t^{(m)} \propto \frac{\mathcal{N}(\hat{\boldsymbol{\mu}}_t, \hat{\boldsymbol{\Sigma}}_t)}{\mathcal{N}(\tilde{\boldsymbol{\mu}}_t, \tilde{\boldsymbol{\Sigma}}_t)}$. The posterior density is then approximated by a Gaussian distribution whose statistical terms are utilized in initializing the particle filter on the CHs that may be active in the next or future time instants.

3.3. FC Particle Filter Implementation in HSN-Type II

In a generic SMC algorithm, when the parameters of the state transition equation are known, the particles are easily generated and hence the main task lies in the calculation of the likelihood for updating the weights. The situation in HSN-Type II is also very similar. The initialization and particle generation proceeds as described in subsection 3.1. The expression for calculating the likelihood is given by

$$p(\mathbf{z}_t|\mathbf{x}_t) = \prod_{c=1}^{C} p(z_{c,t}|\mathbf{x}_t) = \prod_{c=1}^{C} p\left(\sum_{n=1}^{N_c} s_{n,c,t}|\mathbf{x}_t\right).$$

The probability mass functions $p(z_{c,t}|\mathbf{x}_t)$ can be obtained by summing over all possible combinations of sensor transmitted data such that $z_{c,t} = \sum_{n=1}^{N_c} s_{n,c,t}$. However the number of such combinations is relatively large for even small N_c and $z_{c,t}$. To reduce the computational complexity of the problem, we propose to estimate $s_{c,n,t}$ given $\{z_{c,t}, \mathbf{x}_t^{(m)}\}$. The task of assigning $s_{c,n,t} = \{1, 0\}$ is performed as follows:

- Draw the samples of the state vector $\mathbf{x}_t^{(m)}$ and sensor measurements $y_{n,c,t}^{(m)}$ using (4) and (1), respectively.
- $\forall n \in \{1 \cdots N_c\}$ and $c \in \{1 \cdots C\}$, obtain $\omega_{n,c,t} = \frac{1}{M}\sum_m \mathrm{I}(y_{n,c,t}^{(m)} \geq \gamma)$ where $\mathrm{I}(\cdot)$ is the Bernoulli indicator function.
- $\forall c \in \{1 \cdots C\}$ sort the elements of the set $\{\omega_{1,c,t}, \cdots \omega_{N_c,c,t}\}$ in decreasing order and obtain the indices of the first $z_{c,t}$ sensors . Set the value of $s_{c,n,t}$ for the sensors with these indices to `1` and the remaining to `0`.

The likelihood is then approximated as

$$p(\mathbf{z}_t|\mathbf{x}_t) \approx \prod_{c=1}^{C}\prod_{n=1}^{N_c} p\left(s_{n,c,t}|\mathbf{x}_t\right) \qquad (12)$$

and $p\left(s_{c,n,t}|\mathbf{x}_t\right)$ is obtained using (8).

System Parameters	Value
Sensing Field Dimensions	$650m \times 750m$
No of Cluster Units	50
No of Sensors	480
Sensor Threshold γ	56.70
Reference Power Ψ_0	5000
No of particles	2000
Sampling Period	1s
Total Observation Period	60s
Mean of Sensor Noise μ_v	1
Variance of Sensor Noise μ_v	0.01
Observation noise parameter $\sigma_{1,u}^2$	0.1
Observation noise parameter $\sigma_{2,u}^2$	0.2

Table 1. System Parameters and their values

4. SIMULATIONS, RESULTS AND DISCUSSION

In our computer simulations we have considered a sensing field of dimensions $650m \times 750m$ with 50 CHs and 480 sensors in the sensing field deployed randomly (using stratified sampling methods). Sensors were clustered using standard hierarchical clustering algorithms. Table 1 lists the values of the parameters used in simulating the target trajectory and sensor network. In the simulation of the SMC methods, particles were initially drawn from a Gaussian distribution with a known $\mu_0 = [0, 0, 5, 5]^\top$ and a covariance matrix Ξ=diag$(30, 30, 5, 5)$. One hundred target trajectories were generated for which the root mean squared error (RMSE) in estimating the target dynamics was computed.

In Fig 2, we plotted the RMSEs of the two networks for $\alpha = 2.5$ and spatially distributed known and unknown α. We modeled α as a spatially correlated truncated normal random variable $\sim \mathcal{N}_T(\mu_\alpha, \Xi_\alpha, a, b)$, with covariance matrix $\Xi_{\alpha,i,j} = cov(\alpha_i, \alpha_j) = e^{-0.3d_{ij}}$ where d_{ij} represents the Euclidean distance between points i and j. The results show that the error in estimating the position of the target in the 2-D Cartesian coordinate system is around 10m and the errors in estimating the velocities are less than 1.6 m/s. Sensitivity on the knowledge of the attenuation parameter α in the proposed algorithms was more carefully studied. In another experiment, the attenuation parameter α was unknown, but constant for all the sensors. Fig. 3 shows the RMSE errors when α was assumed to be $2, 3,$ and 4 when its true value was 2.5. All these results suggest that when there are large errors in the assumed values of α, the RMSEs may be unacceptably large.

5. CONCLUSION

In this paper we have presented SMC algorithms for target tracking and data fusion in two-tiered HSNs with compressed sensor data. The proposed algorithms show good performance in estimating the dynamics of the target trajectory. We have also presented some simulation results that outline the sensitivity of the proposed algorithms when certain system parameters like the attenuation parameter of the sensor model are unknown.

6. REFERENCES

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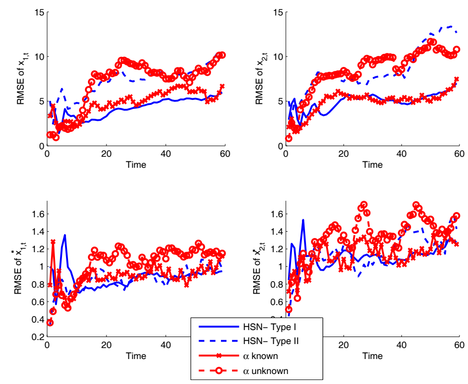

Fig. 2. RMSE in HSNs-Type I and II with $\alpha = 2.5$ and spatially distributed α.

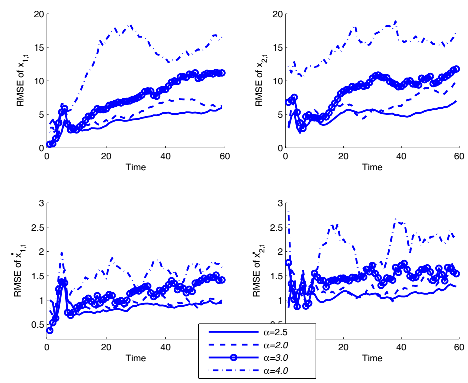

Fig. 3. RMSE in HSNs-Type I, assumed $\alpha = 2.5, 2, 3, 4$, when true value is 2.5

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