Collaborative Sensor Networks with Bayesian Multitarget Tracking and Sensor Localization

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Abstract—We propose a method to track an unknown and variable number of targets without assuming the knowledge of the locations of the sensor nodes in the network. Then, the multitarget tracking and the localization of sensor nodes is performed jointly. As low-power consumption is a requirement in sensor networks, a collaborative estimation scheme is presented, where only a small set of sensors are active while the others remain in an idle state. The proposed technique is based on a Rao-Blackwellized sequential Monte Carlo (SMC) method that takes advantage of the fact that the state space of the unknown variables is separable. The problem is then divided into two parts. The first one generates samples to estimate the number of targets and solves the association uncertainty between measurements and targets; while the second one is a multiple target tracking problem that can be solved with an unscented Kalman filter for each sample. It is shown through simulations that it is possible to track the multiple targets and also get accurate estimates of the unknown locations of the sensor nodes.

Keywords: Sensor networks, multi-target tracking, sensor localization.

I. INTRODUCTION

Sensor networks consist of a collection of low-power, low-cost and autonomous sensor nodes densly deployed in a field under observation. The nodes posses sensing, data processing and communication components and collaborate with each other in order to carry out certain tasks. These features give sensor networks a wide range of surveillance applications, such as monitoring patients in a hospital, environment and habitat monitoring and vehicle tracking.

Applications involving sensor networks usually rely on the assumption that the positions of the nodes are known a priori. This could be achieved by using a predefined deployment of the nodes or to equip each node with a localization device. However, these options are impractical for large and ad hocly deployed sensor networks and increase the cost of the network. An alternative is to let sensor nodes estimate their positions before or while performing their main tasks. This work focuses on the problem of tracking multiple targets in a sensor network using the measurements collected by sensor nodes of unknown positions.

The measurements available for tracking multiple targets are relative to the sensor locations, which makes it natural to consider multitarget tracking and sensor localization jointly.

When dealing with multiple targets, there is uncertainty in the association between targets and measurements. Each sensor produces a set of unlabeled measurements and the tracking algorithm has to estimate which target produced which measurement or if the measurement was due to noise. Once such measurement-target associations are known, the multitarget tracking problem can then be decomposed into multiple single-target tracking problems. In this work, the measurement-target association, the multitarget tracking and the sensor localization are solved jointly within a Bayesian framework. Due to the low-power characteristic of the sensor nodes, a decentralized approach is presented. At each time step, only a small subset of nodes is active, while the others remain in an idle state until required to carry out a specific task.

The problem of jointly multitarget tracking and sensor localization is known as the Simultaneous Localization And Tracking (SLAT) problem.

The first contribution of this work is the proposal of an unscented Kalman filter (UKF) for the SLAT problem when there are a known number of targets present and there is no uncertainty in the origin of the measurements. The second contribution is the extension of the proposed solution to the SLAT problem with multitarget tracking, where a method is proposed for resolving the measurement-target association and the unknown and variable number of targets. The third contribution is a generalization of the Rao-Blackwellized particle filter presented in [8] for multitarget tracking without imposing a maximum number of targets, estimating the positions of the sensor nodes jointly and also dealing with more that one measurement in each time step.

II. SYSTEM DESCRIPTIONS AND PROBLEM FORMULATION

The sensor nodes are assumed to collect measurements, process them and deliver an estimate of the state of the targets (their positions and velocities). As the available power resources are limited the processing and collecting of data must be efficient. Therefore, each target in the field under observation has a small set of active sensor nodes assigned. Every node that does not belong to any set of active sensor nodes remains in an idle state. Each set is responsible for the tracking of a given target called the primary target. All the sensor nodes in the set are aware of each others measurements and have a noisy estimate of the square distance between them through radio connectivity.
A. Problem Formulation

Let $\mathcal{T}_t$ be the set of targets present at time $t$ and $r_t$ its cardinality (the number of targets at time $t$). Also, let $\mathcal{N}_t$ be the set of nodes in the active set at time $t$ and $S$ its cardinality, where it is assumed that the number of nodes in $\mathcal{N}_t$ is fixed and does not depend on time. We denote by $\gamma_{t,j} = \{x_{t,j}, i\in\mathcal{T}_t \| \gamma_{t,j} \in \mathcal{N}_t\}$, the state of the system at time step $t$, where $\| \gamma_{t,j}$ is the concatenation operator, $x_{t,j}$ is the state (position and velocity) of the $j$th target at time $t$ and $\gamma_{t,j}$ the state (position) of the $j$th sensor node at time $t$.

It is assumed that each target moves independently according to a Markovian transition dynamic,

$$x_{t,i} = F_{t,i} x_{t-1,i} + u_{t,i}, \quad \forall i \in \mathcal{T}_t \cap \mathcal{T}_{t-1}. \quad (1)$$

The function $F_{t,i}(\cdot)$ will be defined according to a motion model for each target. The noise term $u_{t,i}$ is assumed to be white. When a new target is considered ($i \in \mathcal{T}_t \setminus \mathcal{T}_{t-1}$) its prior information if available should be incorporated by the tracking algorithm.

Moreover, sensor nodes are also assumed to move with a Markovian transition dynamic,

$$\gamma_{t,i} = F_{t,i} \gamma_{t-1,i} \quad \forall i \in \mathcal{N}_t. \quad (2)$$

In the most general case, the function $F_{t,i}(\cdot)$ depends on the position of all nodes in the previous time ($t-1$).

Each node in the set of $S$ sensor nodes produces a set of measurements available at each time step. Every measurement can arise from a target if it is detected or it can be spurious clutter noise. The observations are unlabeled, making the associations between targets and measurements a major challenge.

Let $g_{t,l}^k(j)$ be the $j$th measurement from the $l$th sensor node at time $t$. A measurement-target association $c_{t,l}^k(j)$ is assigned to the measurement. Given that there are $r_t$ targets present, $c_{t,l}^k(j)$ takes values in the set $\{0\} \cup \mathcal{T}_t$.

$$c_{t,l}^k(j) = \begin{cases} 0, & \text{if } g_{t,l}^k(j) \text{ is due to clutter}, \\ k, & \text{if } g_{t,l}^k(j) \text{ is due to the } k\text{th target}, \quad \forall i \in \mathcal{N}_t. \quad (3) \end{cases}$$

If the measurement is generated by the target $c_{t,l}^k(j) = i$ with $i \neq 0$ then $g_{t,l}^k(j)$ is a function $H_{t,l}^k(\cdot)$ of the $i$th target state, the position of the $l$th node and some noise term $w_{t,l}^k(j)$. On the other hand, if $c_{t,l}^k(j) = 0$, the measurement was due to clutter and is a random variable sampled from a distribution $P_{l}(\cdot)$. That is,

$$g_{t,l}^k(j) = \begin{cases} H_{t,l}^k(x_{t,l}, c_{t,l}^k(j), \gamma_{t,l}, w_{t,l}^k(j)), & \text{if } c_{t,l}^k(j) \neq 0, \\ \sim P_{l}(\cdot), & \text{otherwise}. \quad (4) \end{cases}$$

For $l \in \mathcal{N}_t$, let $N_l^k$ be the total number of measurements collected by the $l$th sensor node at time $t$. Then, let $y_t^l = [y_{t,l}^1(1)...y_{t,l}^1(N_l^k)]^T$ be the vector of measurements collected by the $l$th sensor node and $c_t^l = [c_{t,l}^1(1)...c_{t,l}^1(N_l^k)]^T$ the vector of measurement-target associations. Furthermore, let $y_t = \{y_t^l\}_{l \in \mathcal{N}_t}$ be the vector of the measurements collected by all the sensor nodes in $\mathcal{N}_t$ and $c_t = \{c_t^l\}_{l \in \mathcal{N}_t}$ their measurement-target associations. The number of targets $r_t$ and the measurement-target associations $c_t$ are unknown. Moreover, when a target disappears, a variable $d_t$ is introduced to indicate which target disappears. As will be explained in Section IV, the vectors $d_t = d_t^11$ and $r_t = r_t^1$ are used instead of the scalars $d_t$ and $r_t$, where $1$ is a vector of ones with the same dimension as the number of measurements at time $t$. Then, to estimate the joint state of the multiple targets and the sensor locations $x_t$, the estimation of $z_t = \{r_t, c_t, d_t\}$ is also performed.

Within the framework described above, the objective is to perform an online estimation of the posterior distribution of the joint state of the multiple targets and the sensor locations, the number of targets, the measurement-target associations and the indicator variable $p(x_t, z_t|y_{1:t})$ at time $t$ based on the measurements history $y_{1:t}$ at densely deployed sensor nodes.

B. Specific Dynamics Model

Each target is assumed to be moving in a two-dimensional plane independently with a constant velocity model. For the $i$th target, with $i \in \mathcal{T}_t \cap \mathcal{T}_{t-1}$, its state evolves as

$$x_{t,i} = F_{t,i} x_{t-1,i} + G_{t,i} u_{t,i}, \quad i \in \mathcal{T}_t \cap \mathcal{T}_{t-1}. \quad (5)$$

The zero-mean Gaussian random vector $u_{t,i}$ with covariance matrix $R_{t,i}$ allows to model random maneuvering of the target under observation [9]. Calling $\tau$ the length of a time step, $I_2$ the $2 \times 2$ identity matrix, and using the Kronecker operator $\otimes$, the matrices $F_{t,i}$ and $G_{t,i}$ are given by

$$F_{t,i} = \begin{bmatrix} 1 & \tau \\ 0 & 1 \end{bmatrix} \otimes I_2 \quad \text{and} \quad G_{t,i} = \begin{bmatrix} \frac{\tau^2}{2} \\ \tau \end{bmatrix} \otimes I_2. \quad (6)$$

The set of sensors is restricted to evolve according to two rules: Either the set at time $t$ is the same as that at time ($t-1$); or the set at time $t$ only differs by one element from that at time ($t-1$). A criterion to choose one of these two alternatives will be presented in Section IV-B. In the first case, the state evolves according to

$$\gamma_{t,j} = \gamma_{t-1,j}, \quad j \in \mathcal{N}_t. \quad (7)$$

In the second case, a new node $n$ replaces an existing node $m$ in the active set. Then, the state evolution is

$$\gamma_{t,j} = \gamma_{t-1,j}, \quad j \neq m, \quad \text{and} \quad \gamma_{t,m} = g(\{\gamma_{t-1,i}\}_{i \in \mathcal{N}_{t-1}}), \quad (8)$$

where $g(\cdot)$ is a trilateration function. For this function, it is assumed that each node in the set $\mathcal{N}_{t-1}$ can communicate with the node $m$ and obtain a noisy estimate of the square distance between them.

C. Specific Measurement Model

Each sensor node generates a set of measurements. For each target within a defined range of each node, there is a probability $(1 - P_d)$ that the target goes undetected and moreover, a measurement can be due to noise. The $j$th measurement of the $i$th sensor $y_{t,i}^j(j)$ at time $t$ is then assumed to be originated from a target or due to clutter.
The function $H(.)$ in (4) is chosen to reflect the measurement of the power of a radio signal emitted by the target. In this case, the received power exponentially decays with the relative distance between the sensor position $\gamma_{t,k}$ and the target position $x_{t,k}^{p}$, 
\[ d(x_{t,k}, \gamma_{t,k}) = \|x_{t,k}^{p} - \gamma_{t,k}\|, \]
where the state of the $k$th target at time $t$ is the concatenation of its position $x_{t,k}^{p}$ and its velocity $\gamma_{t,k}$. Assuming the $k$th target generates the $j$th measurement on the $l$th sensor node, then the function $H(.)$ in (4) is given by
\[ y_{l}^{t}(j) = K - 20\eta \log_{10}(d(x_{t,k}, \gamma_{t,l})) + u_{l}^{t}(j), \quad (9) \]
where $K$ is the transmission power and $\eta \in [2, 3]$ is the path loss exponent.

On the other hand, the measurements that are due to clutter are considered to be uniformly distributed in the measurement area $A$ of each sensor. The number of such measurements is assumed to have a Poisson distribution with parameter $\lambda$.

### III. BAYESIAN FILTERING

Consider the following general dynamic system with state variable $x_{t}$ and measurement variable $y_{t}$.

- initial state model: $p(x_{0})$,
- state transitions model: $p(x_{t}|x_{t-1})$, $\forall t \geq 1$,
- measurement model: $p(y_{t}|x_{t})$, $\forall t \geq 1$.

In order to estimate $x_{t}$ for each time $t$ given that $y_{1:t} \equiv [y_{1}, \ldots, y_{t}]$ is observed, the posterior distribution of the state given the observation history, i.e., $p(x_{t}|y_{1:t})$, is needed. By Bayes’ theorem, it is straightforward to obtain the following recursion
\[ p(x_{t}|y_{1:t-1}) = \int p(x_{t}|x_{t-1})p(x_{t-1}|y_{1:t-1})dx_{t}, \quad (11) \]
\[ p(x_{t}|y_{1:t}) \propto p(y_{t}|x_{t})p(x_{t}|y_{1:t-1}). \]

**Kalman Filter:** When the underlying state transition and measurement models in (10) are linear and Gaussian, the recursion in (11) is solved by the Kalman Filter (KF) [9]. The KF provides an efficient recursive means to compute
\[ \hat{x}_{t|t} = E \{x_{t}|y_{1:t}\}, \quad \text{and} \quad P_{t|t} = E \{(x_{t} - \hat{x}_{t|t})(x_{t} - \hat{x}_{t|t})'\}, \]
which completely characterize $p(x_{t}|y_{1:t})$.

**Unscented Kalman Filter:** When the underlying state transition and measurement models are nonlinear, the KF is not applicable. Moreover, the exact recursion in (11) usually involves a high dimensional integration, which is infeasible in practice. The unscented Kalman filter (UKF) [10] approximates the posterior distribution $p(x_{t}|y_{1:t})$ by a Gaussian with a deterministic sampling technique known as the unscented transform (UT).

**Sequential Monte Carlo (SMC) Methods:** When a more accurate approximation for the posterior distribution is needed, SMC methods [11] can be used, with a higher algorithmic complexity. The SMC methods approximate the posterior distribution $p(x_{0:t}|y_{1:t})$ with a weighted representation. In order to do so, a distribution $\pi(x_{0:t}|y_{1:t})$ called importance distribution is introduced such that it is easy to sample and its support includes the support of $p(x_{0:t}|y_{1:t})$. Then, as it is easy to take samples $x_{0:t}$ from the importance distribution, it is possible to approximate $\pi(x_{0:t}|y_{1:t})$ with a Parzen window method and to approximate $p(x_{0:t}|y_{1:t})$ as
\[ p(x_{0:t}|y_{1:t}) \approx \sum_{i=1}^{N} \tilde{w}(x_{0:t}^{i}) \delta(x_{0:t}^{i} - (x_{0:t})), \quad (12) \]
with $\tilde{w}(x_{0:t}^{i}) = \frac{w(x_{0:t}^{i})}{\sum_{i=1}^{N} w(x_{0:t}^{i})}$ and $w(x_{0:t}) = p(x_{0:t}|y_{1:t}), p(x_{0:t}^{i}|y_{1:t})$.

In order to obtain an online estimation procedure, the importance density function is chosen so that when sampling the state $x_{t}$, the past $\{x_{0:t-1}\}$ state samples are kept unchanged. This also leads to a recursive formula for the weights.

The variance of the weights increases over time which is known as the degeneracy phenomenon. One option against this is to perform resampling in order to discard ineffective samples and multiply the effective ones.

**Rao-Blackwellized SMC:** The Rao-Blackwellized particle filter [12] is an SMC method that improves the performance of the posterior distribution approximation when a substructure of the posterior can be expressed analytically. If the state can be divided in two sub-spaces $x_{t}$ and $z_{t}$, samples of $z_{t}$ are obtained using a standard SMC procedure and afterwards the distribution of $x_{t}$ is updated with the exact filter, conditioned on $z_{t}$. As a smaller space is sampled, fewer particles are needed to achieve a similar approximation to the joint distribution.

### IV. JOINT MULTITARGET TRACKING AND SENSOR LOCALIZATION

Each set of sensor nodes is assigned to a single target and tracks it independently of the other targets if those targets are far away. However, when the secondary targets are close, they also generate measurements in the set of sensor nodes and therefore the set must be able to track an unknown and variable number of targets. Moreover, as multiple targets are present and measurements may also be due to clutter, the set of active nodes has to determine the origin of each measurement. Therefore, the algorithm should also estimate the number of targets to track $r_{t}$, the measurement-target associations $c_{t}$ and, if there is a target disappearing, its identity $d_{t}$. Let $z_{t} = \{r_{t}, c_{t}, d_{t}\}$, then the objective is to approximate $p(x_{t}, z_{t}|y_{1:t})$ at time $t$ based on the measurements $y_{1:t}$.

In order to perform the estimation, the Rao-Blackwellized particle filter is employed to take samples of $z_{0:t}$ given the observation history $y_{1:t}$ to approximate $p(x_{0:t}|y_{1:t})$; and afterwards, the distribution of $x_{t}$ given $z_{t}^{i}$ and the observation history $y_{1:t}$, i.e., $p(x_{t}|z_{0:t}^{i}, y_{1:t})$, is approximated with an UKF.

#### A. Approximation of $p(z_{1:t}|y_{1:t})$

When secondary targets start generating measurements in the set of sensor nodes, the set has to be able to estimate the number of targets $r_{t}$ to handle. This variable is modeled such that it can increase in one, stay unchanged or decrease in one in each time step, i.e.,
\[ p(r_{t}|r_{t-1}) = \begin{cases} P_{b}, & \text{if } r_{t} - r_{t-1} = 1, \\ 1 - P_{b} - P_{d}, & \text{if } r_{t} - r_{t-1} = 0, \\ P_{d}, & \text{if } r_{t} - r_{t-1} = -1. \end{cases} \quad (13) \]
When $r_{t-1} - r_{t} = 1$, it is unknown which target is the one that disappears. Therefore, the variable $d_{t}$ is introduced such that it...
takes values in the set \( T_{t-1} \cup \{0\} \), where \( d_t = i \) means that the \( i \)-th target disappears and \( d_t = 0 \) when \( r_{t-1} \neq r_t \). As the set of active nodes is in charge of tracking a primary target, the probability that \( d_t = 1 \) is set to zero. Given \( r_t \) and \( r_{t-1} \), the distribution of \( d_t \) is

\[
d_t \sim \mathcal{U}_D, \quad \text{if } r_{t-1} - r_t = 1, \quad \text{(14)}
\]

and \( d_t = 0 \), otherwise,

where \( \mathcal{U} \) stands for the uniform distribution and \( D = T_{t-1} \setminus \{1\} \).

Each target produces a measurement in a node if it is inside its range with probability \( P_D \). Measurements can also arise from clutter. Then the measurement-target associations have to be estimated. It is assumed that each target can generate at most one measurement in each sensor node, so given the previous associations for a given sensor \( l \) and the number of targets \( r_t \), at time \( t \)

\[
c_t(j) \sim \mathcal{U}_E, \quad \text{(15)}
\]

where the set \( E = \{\{1 \ldots r_t\} \setminus P^l_t\} \cup \{0\} \), and \( P^l_t \) is the set of previous associations \( \{c^l_t(i)\}_{i=1}^{j-1} \) for sensor node \( l \) at time \( t \).

As the number of observations in a time step increases, the possible associations between targets and observations become a combinatorial problem with high computational complexity. In order to avoid this problem, a sequential treatment of measurements is proposed. Then, the estimation procedure is reduced to processing one measurement at a time. For that purpose, the vectors \( r_t = r_{t-1} \) and \( d_t = d_{t-1} \) are introduced, where 1 is a vector with ones as components and its dimension is the same as the number of measurements at time \( t \).

The random variables \( r_t(j), c_t(j) \) and \( d_t(j) \) are grouped in a new variable \( z_t(j) \). An SMC method is used to approximate \( p(z_{0:t-1}, z_t(1:j)|y_{1:t-1}, y_t(1:j)) \). When the last measurement of the set of measurements is processed, then an approximation to \( p(z_{1:t}|y_{1:t}) \) is obtained.

**Importance Distribution:** The importance distribution to sample from is chosen to be the prior distribution. Then, for the first measurement in the set, we have the following importance density

\[
p(z_t(1)|z_{1:t-1}) = p(c_t(1)|d_t(1), r_t(1), z_{1:t-1}) \quad \text{(16)}
\]

\[
p(d_t(1)|r_t(1), z_{1:t-1})p(r_t(1)|z_{1:t-1}),
\]

\[
= p(c_t(1)|d_t, r_t)p(d_t|r_t, r_{t-1})p(r_t|r_{t-1}).
\]

On the other hand, when processing the \( j \)-th measurement (with \( j > 1 \)) in the set of measurements collected by the sensor nodes, the importance density is

\[
p(z_t(j)|z_{1:t-1}, z_t(1:j-1)) = p(c_t(j)|c_t(1:j-1), d_t, r_t)
\]

\[
\delta(r_t)\delta(d_t),
\]

where it was used the fact that \( p(r_t(j)|r_{1:t-1}, r_t(1:j-1)) = p(r_t(j)|r_t) = \delta(r_t) \) for \( j > 1 \). Analogously for \( p(d_t(j)|d_t) \).

**Weights Update:** When the importance distribution is chosen to be the prior distribution, the weights of the particles are proportional to the likelihood \( p(y_t(j)|z_{1:t-1}, z_t(1:j), y_{1:t-1}, y_t(1:j-1)) \) of the measurement being processed times the weight for the previous processed measurement.

For the first measurement of the set, the likelihood of the measurement \( y_t(1) \) is given by \( p(y_t(1)|z_{1:t-1}, z_t(1), y_{1:t-1}) \). If \( z_t(1) \) is such that \( c_t(1) = 0 \), then the measurement is due to clutter, and the likelihood is \( 1/A \), where \( A \) is the measurement area of the sensor nodes. On the other hand, if \( c_t(1) \neq 0 \), the likelihood of the measurement can be approximated with a Gaussian of mean \( \bar{y} \) and variance \( \sigma_y^2 \). Given \( c_{1:t-1}, r_{1:t-1}, d_{1:t-1} \) and \( y_{1:t-1} \), an estimate of the mean \( \bar{\alpha}_{t-1} \) and its covariance matrix \( P_{t-1} \) are available. Then, \( \bar{y} \) and \( \sigma_y^2 \) can be computed using the UT discussed in III.

On the other hand, when processing the \( j \)-th measurement (with \( j > 1 \)) of the set of measurements, the likelihood to be computed is \( p(y_t(j)|z_{1:t-1}, z_t(1:j), y_{1:t-1}, y_t(1:j-1)) \). Once again, if \( c_t(j) = 0 \), the measurement is due to clutter, and the likelihood is \( 1/A \). If \( c_t(j) \neq 0 \), a similar approach is taken. Given \( c_{1:t-1}, r_{1:t-1} \) and \( d_{1:t-1} \), an estimate of the mean \( \bar{\alpha}_{t-1} \) and its covariance matrix \( P_{t-1} \) are available. As \( c_t(1:j-1), r_{1:t}, d_{1:t}, \) and \( y_t(1:j-1) \) are also given, the UKF gives an estimate of \( \bar{\alpha}_t \) and its covariance matrix \( P_{t} \). Then, \( \bar{y} \) and \( \sigma_y^2 \) can be computed using the UT and the observation equation.

**B. Sensor Selection**

Let a neighboring node be defined as a node not belonging to \( N_{t-1} \) but with radio connectivity to every node in \( N_{t-1} \). Then, every node in the set of active nodes \( N_{t-1} \) have a noisy estimate of the square distances to each sensor node in the set of neighboring nodes \( M_t \) through the radio connectivity. Therefore, it is possible to have a raw estimate of the position of each node in \( M_t \). On the other hand, the set of active nodes is able to make a one step ahead prediction of the position of the primary target. Then, it is possible to evaluate if one of the neighboring nodes is closer to the predicted position of the target than one of the nodes in the set of active nodes. If so, the node no longer used is set to an idle state and the new node is added to the set \( N_t \). The number of new nodes added to the set of active nodes is restricted to be less or equal to one. This process can be carried out periodically.

**C. Summary of the Algorithm**

- Initialize the algorithm
  - Assign a set of active nodes for each target and estimate the position of the targets and the positions of the sensor nodes with priors.
- For each time step \( t \),
  - If the sensor set has remained unchanged for a time duration larger than a threshold, enter the sensor selection stage.
  - Sample \( r_t \) according to (13).
  - Sample \( d_t \) according to (14).
  - For every measurement collected by the sensor nodes in the set of active nodes,
    - For every sample stream,
      - Sample \( c_t(j) \) according to (15).
      - Compute its weight, as discussed in Section IV-A.
    - Resample the particles if needed.
    - Compute \( \bar{\alpha}_t \) for every sample stream with the UKF, as discussed in Section III.
V. SIMULATION RESULTS

Computer simulations are carried out to show the performance of the proposed algorithm. The experimental setting consists of two moving targets. Initially, the distance between the targets is such that each sensor set does not collect measurements from the secondary target. However, as time evolves, the targets start getting closer and both sets collect measurements from the secondary target.

The following parameters are used in the simulations. The field has a dimension of \(600 \times 300m^2\) and 500 randomly scattered sensor nodes. The active set consists of 6 sensor nodes and each node can sense a target if it is within a range of \([1m, 50m]\). Moreover, if the target is inside the range of a node, there is a probability of detecting it of \(P_D = 0.99\). The variance of the measurement noise is 1. On the other hand, measurements can arise from clutter. The number of such measurements is given by a Poisson distribution of \(\lambda = 0.1\).

The time step is chosen to be \(\tau = 1\) second. For the constant velocity model, \(R_{t,k}\) is set to 0.03\(^2 I_2\). The prior for the initial state is Gaussian with true mean and the covariance matrix is \(P_0 = \text{diag}(0.005^2, 0.005^2, 0.00005^2, 0.00005^2, 10^{-9}, \ldots, 10^{-9})\). The number of sample streams used in the SMC algorithm is 25.

In Fig. 1, a single run of the algorithm is shown. Both targets move from left to right. Fig. 1 shows the estimation performed by the first sensor set that is in charge of one of the targets. Both the estimation for its main target and the estimation for the secondary target are shown. The estimated positions of the sensor nodes are also illustrated. It can be seen that our algorithm is able to accurately track each of the targets and locate the sensor nodes.

The algorithm is compared with a second algorithm that estimates the tracks of the targets given that the positions of the sensor nodes are known. Fig. 2 shows the result of such comparison. The second algorithm is based on our algorithm but it has been adapted to make use of the true position of the sensor nodes. It is seen in the figure that the performances are similar even though our algorithms is estimating the sensor nodes and the multiple tracks at the same time.

VI. CONCLUSIONS

In this paper, we have proposed a Bayesian framework to perform multiple target tracking and sensor localization jointly in a collaborative scheme where sensor nodes remain idle until requested to perform a specific task. Moreover, as the sensor nodes are low-cost devices, it is assumed that they lack a localization component and as a consequence, their positions are estimated jointly with the multitarget tracking task. Our first contribution is the proposal of an UKF to solve the multitarget tracking and sensor localization tasks when the number of targets is known and there is no uncertainty in the origin of the measurements. The second contribution resides on the extension of the proposed solution in scenarios where there is an unknown and time-varying number of targets to track. Finally, we have presented a Rao-Blackwellized SMC capable of dealing with a set of observations in each time step. It is shown by computer simulations that the proposed method is able to track multiple targets and to obtain an accurate estimation of the sensor locations.

Fig. 1. Tracking and localization behavior in a sensor network with two targets.

Fig. 2. Comparison between the joint estimation and localization algorithm and a multitarget tracking algorithm using sensor nodes with known positions.

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