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SEQUENTIAL MARKOV CHAIN MONTE CARLO FOR MULTI-TARGET TRACKING WITH CORRELATED RSS MEASUREMENTS

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ABSTRACT

In this paper, we present a Bayesian approach to accurately track multiple objects based on Received Signal Strength (RSS) measurements. This work shows that taking into account the spatial correlations of the observations caused by the random shadowing effect can induce significant tracking performance improvements, especially in very noisy scenarios. Additionally, the superiority of the proposed Sequential Markov Chain Monte Carlo (SMCMC) method over the more common Sequential Importance Resampling (SIR) technique is empirically demonstrated through numerical simulations in which multiple targets have to be tracked.

Index Terms*— *Tracking, Correlated shadowing, Bayesian inference, Sequential MCMC.

1. INTRODUCTION

Mobile multi-target tracking is one the primary challenges of a number of fields, including that of wireless cellular communication networks. In this area, the main structure of a system will feature target nodes whose kinematic states are unknown and need to be estimated; and sensor nodes receiving some type of noisy information about the target nodes, from which an estimation of their states can be inferred.

A variety of methods have been developed in order to solve this localization problem. The more common range-based methods (as opposed to range-free methods) depend on the distances between nodes, through measurements of received signal strengths (RSS), signal time-of-arrivals (ToA) [1] or angle-of-arrivals (AoA) [2] originating from the targets. Both ToA and AoA approaches allow for accurate distance estimations leading to good localization, however ToA requires synchronized clocks on the target nodes, while AoA requires an array of antennas and is still sensitive to errors due to multipath, making them costly solutions. The received signal strength technique [3] is a much more direct and simple approach, with low implementation costs ; as such, it is a recurrent subject of performance optimization attempts. Taking into account the shadowing correlation ([4] ; Gudmunson's model [5]) between different nodes (targets or sensors), which capitalizes on the fact that in a given environment, closeby areas present more or less similar behaviors with regard to shadowing, and may thus be modeled as highly correlated, is one such way of improving this technique. A few examples of research include [6] which studies the combination of measurement correlation and shrinkage estimation of the covariance matrix for significant performance improvements, but is limited to the static case. In [7–10] the measurement correlations are taken into account and refined particle filtering (or Sequential Importance Resampling) algorithms are implemented, resulting in high accuracy localization, however they inherently suffer from the limitations of the particle filtering approach, which, although known to be an effective way of solving non-linear problems, performs poorly in high-dimensional state-spaces [11].

In this paper, we design a Bayesian solution to this problem based on a Sequential Markov Chain Monte Carlo (SMCMC) algorithm, allowing for more robust and overall better performance than particle filtering. Additionally, we take into account the shadowing correlations both spatially and in time, that is, between either current or past positions of any targets. This allows for performance improvements both due to the correlations in time between positions of a single target, and due to the correlations between trajectories of different targets which may cross at some point in time. The combination of these two features thus has a good potential for overall robustness in tracking performance in a wide range of scenarios.

The paper is structured as follows. Section 2 details the choice of the target and observation models. Section 3 explains the Bayesian framework used and the proposed SMCMC solution. Simulation results using synthetic data are presented and analyzed in Section 4, while Section 5 highlights the main conclusions of this work.

2. TARGET AND OBSERVATION MODELS

2.1. Target state and motion models

In a 2-dimensional (2-D) network, the kinematic state of a single target at discrete time step t may be defined as a vector of positions and velocities $\mathbf{x}_t = [x_t, y_t, \dot{x}_t, \dot{y}_t]$, although it could also contain accelerations or other variables of interest. The kinematic state $\{\mathbf{x}_{t,1:N}\}_{t\in\mathbb{N}^*} = \{[(\mathbf{x}_{t,1})^T, (\mathbf{x}_{t,2})^T, \dots, (\mathbf{x}_{t,N})^T]\}_{t\in\mathbb{N}^*}$ of a set of N targets is considered to be a stochastic Markov process such that at any time step t, the transition probability density function (pdf) $p(\mathbf{x}_{t,1:N}|\mathbf{x}_{1:t-1,1:N}) = p(\mathbf{x}_{t,1:N}|\mathbf{x}_{t-1,1:N})$ is known and can either be evaluated point-wise or sampled from.

2.2. Correlated observation model

Consider a set of N targets evolving from time 1 to time T, $\mathbf{x}_{1:T,1:N}$, and a set of M immobile sensors $\mathbf{s} = [\mathbf{s}^1, \cdots, \mathbf{s}^M]^T$ where $\mathbf{s}^i = [s_x^i, s_y^i]^T$ is the position of the i-th sensor for $i \in \{1, \dots, M\}$. At time $t \in \{1, \cdots, T\}$, a target $j \in \{1, \cdots, N\}$ transmitting a signal with power $p_{t,j}$ causes a sensor i to receive a signal with power $p_{t,j}^i$ (the data association problem is assumed to be resolved, for example it could be assumed that the targets emit during preassigned epochs) ; the corresponding path-loss can be expressed as

$$\mathcal{L}_{t,j}^i = 10\log_{10} p_{t,j} - 10\log_{10} p_{t,j}^i$$

The observed path-loss $y^i_{t,j}$ at the sensor can empirically be modeled [12, 13] as

$$y^i_{t,j} = \mathcal{L}^i_{t,j} - \mathcal{L}_0 = 10\alpha \log_{10} d(\mathbf{x}_{t,j}, \mathbf{s}^i) + w^i_{t,j}$$

where

$$d(\mathbf{x}_{t,j}, \mathbf{s}^i) = \sqrt{(x_{t,j} - s^i_x)^2 + (y_{t,j} - s^i_y)^2} \tag{1}$$

corresponds to the Euclidean distance between the position of the j-th target at time t and the i-th sensor. $\mathcal{L}_0$ is the path-loss at a reference distance of usually 1 meter away from the sensor ; α is the path-loss exponent (PLE) assumed known (or previously estimated in a real application) ; and $w^i_{t,j} \sim \mathcal{N}(0, (\sigma^i_j)^2)$ is the realization of a random variable modeling the log-normal shadowing effect, with σ^i_j the shadowing standard deviation associated with the link between the i-th sensor and the j-th target. σ^i_j is assumed to be constant over time.

In order to account for the spatio-temporal shadowing correlations between two positions within the network, we use the Gudmunson model [5]. Thus the correlation between the j-th target at time r and the k-th target at time s, for $(j,k) \in \{1,\dots,N\}$ and $(r,t) \in \{1,\dots,T\}$, is:

$$\rho(\mathbf{x}_{r,j}, \mathbf{x}_{t,k}) = \exp\left(-\frac{d(\mathbf{x}_{r,j}, \mathbf{x}_{t,k})}{D_c}\right)$$

where D_c is the decorrelation distance used in the Gudmundson model, which depends on the environment and is assumed to be known or previously estimated.

By defining :

- $f^i(\mathbf{x}_{t,j}) = 10\alpha \log_{10}(d(\mathbf{x}_{t,j}, \mathbf{s}^i))$ the exact path-loss between the position of $\mathbf{x}_{t,j}$ and that of $\mathbf{s}^i$.
- $\rho^i(\mathbf{x}_{r,1:N}, \mathbf{x}_{t,1:N})$ a $N \times N$ matrix whose (j,k) term $[\rho^i(\mathbf{x}_{r,1:N}, \mathbf{x}_{t,1:N})]_{j,k} = \sigma^i_j \sigma^i_k \exp\left(-\frac{d(\mathbf{x}_{r,j}, \mathbf{x}_{t,k})}{D_c}\right)$ represents the covariance between the positions of $\mathbf{x}_{r,j}$ and $\mathbf{x}_{t,k}$.

the collection of all the path-loss measurements observed at the i-th sensor until time t is therefore distributed according to the following multivariate Gaussian density $p(y^i_{1:t,1:N}|\mathbf{x}_{1:t,1:N})$:

$$y^i_{1:t,1:N} = \begin{bmatrix} y^i_{1,1} \\ \vdots \\ y^i_{1,N} \\ \\ \vdots \\ \\ y^i_{t,1} \\ \vdots \\ y^i_{t,N} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} f^i(\mathbf{x}_{1,1}) \\ \vdots \\ f^i(\mathbf{x}_{1,N}) \\ \\ \vdots \\ \\ f^i(\mathbf{x}_{t,1}) \\ \vdots \\ f^i(\mathbf{x}_{t,N}) \end{bmatrix}, \mathbf{R}^i_t \right) \tag{2}$$

with $\mathbf{R}^i_t$ the $(N \times t, N \times t)$ observation covariance matrix which introduces correlations in the measurements due to the close proximity of target positions, both "spatially" at a given time step and "spatio-temporally" between positions of different targets from different time steps, and can be expressed in blocks as:

$$\mathbf{R}^i_t = \begin{bmatrix} \rho^i(\mathbf{x}_{1,1:N}, \mathbf{x}_{1,1:N}) & \cdots & \rho^i(\mathbf{x}_{1,1:N}, \mathbf{x}_{t,1:N}) \\ \\ \vdots & \ddots & \vdots \\ \\ \rho^i(\mathbf{x}_{t,1:N}, \mathbf{x}_{1,1:N}) & \cdots & \rho^i(\mathbf{x}_{t,1:N}, \mathbf{x}_{t,1:N}) \end{bmatrix} \tag{3}$$

Finally, each sensor is supposed independent from all other sensors regarding measurement correlations - this is justified by considering scenarios where the sensor positions are immobile and sufficiently far apart from each other. Thus the joint pdf of the measurements from several sensors can be calculated as the product of the pdfs of the measurements from each one of these sensors:

$$p(y^{1:M}_{1:t,1:N}|\mathbf{x}_{1:t,1:N}) = \prod_{i=1}^{M} p(y^i_{1:t,1:N}|\mathbf{x}_{1:t,1:N})$$

3. PROPOSED BAYESIAN SOLUTION

3.1. Recursive inference

The aim of the Bayesian inference is to recursively estimate the states of the sequence of targets by computing the expectation of its joint posterior density. At time t, this posterior density can be deduced recursively as a function of its expression from the previous time step $t-1$:

$$\begin{aligned} &p(\mathbf{x}_{1:t,1:N}|y^{1:M}_{1:t,1:N}) \propto \\ &\textstyle\prod_{i=1}^{M} p(y^i_{t,1:N}|y^i_{1:t-1,1:N}, \mathbf{x}_{1:t,1:N}) p(\mathbf{x}_{t,1:N}|\mathbf{x}_{t-1,1:N}) \\ &\times p(\mathbf{x}_{1:t-1,1:N}|y^{1:M}_{1:t-1,1:N}) \end{aligned} \tag{4}$$

However, this density is intractable mainly due to the nonlinear relationship of the hidden state in the observations and therefore needs to be approximated. In this posterior distribution of interest, the likelihood is obtained from Eq. (2) using classical conditional properties of the multivariate Gaussian distribution:

$$p(y^i_{t,1:N}|y^i_{1:t-1,1:N}, \mathbf{x}_{1:t,1:N}) = \mathcal{N}\left(\boldsymbol{\mu}^i_t, \boldsymbol{\Sigma}^i_t\right) \tag{5}$$

where

$$\begin{aligned} \boldsymbol{\mu}^i_t &= \boldsymbol{\mu}_2 + \boldsymbol{\Sigma}_{2,1}\boldsymbol{\Sigma}^{-1}_{1,1}(\mathbf{z} - \boldsymbol{\mu}_1) \\ \boldsymbol{\Sigma}^i_t &= \boldsymbol{\Sigma}_{2,2} - \boldsymbol{\Sigma}_{2,1}\boldsymbol{\Sigma}^{-1}_{1,1}\boldsymbol{\Sigma}_{1,2} \end{aligned} \tag{6}$$

with

$$\begin{aligned} &\mathbf{z} = y^i_{1:t-1,1:N} \\ &\boldsymbol{\mu}_1 = [f^i(\mathbf{x}_{1,1}), \cdots, f^i(\mathbf{x}_{1,N}), \cdots, f^i(\mathbf{x}_{t-1,1}), \cdots, f^i(\mathbf{x}_{t-1,N})]^T \\ &\boldsymbol{\mu}_2 = [f^i(\mathbf{x}_{t,1}), \cdots, f^i(\mathbf{x}_{t,N})]^T \\ &\boldsymbol{\Sigma}_{1,1} = \mathbf{R}^i_{t-1} \\ &\boldsymbol{\Sigma}_{2,1} = [\rho^i(\mathbf{x}_{t,1:N}, \mathbf{x}_{1,1:N}), \cdots, \rho^i(\mathbf{x}_{t,1:N}, \mathbf{x}_{t-1,1:N})] \\ &\boldsymbol{\Sigma}_{1,2} = [\rho^i(\mathbf{x}_{1,1:N}, \mathbf{x}_{t,1:N}), \cdots, \rho^i(\mathbf{x}_{t-1,1:N}, \mathbf{x}_{t,1:N})]^T \\ &\boldsymbol{\Sigma}_{2,2} = \rho^i(\mathbf{x}_{t,1:N}, \mathbf{x}_{t,1:N}) \end{aligned}$$

Given that any measurement is dependent on all of the other measurements at any time step, the sizes of the mean vector and covariance matrix of the observation defined in Eq. (2) grow with time.

As a consequence, the cost of the computation of the likelihood in Eq. (6) that will be required in the filtering algorithm increases with time. In this paper, we therefore propose to use a strategy in order to have a constant computational cost by using a restriction of the size of the used history of positions, for instance through a sliding time window. One drawback of such an approximation is that it could imply the loss of interesting correlation information in cases where some targets approach past trajectories of some other targets (or themselves). Indeed, although the most significant correlations may often intuitively be the ones between positions of a same target at close time steps, simply due to their inherent proximity compared to the proximity of positions from different targets, this still depends on the chosen target motion model. It is likely to be the case if the targets move completely independently, which is clearly not always a correct assumption in real scenarios. However, the sliding time window approximation may also help in avoiding possible numerical problems in the evaluation of the likelihood (due to the inversion of a large covariance matrix). By defining the size of this sliding time window as t_{window}, the computation of the likelihood in Eq. (6) will involve a modified covariance matrix of size $(N \times (t_{window}+1), N \times (t_{window}+1))$ since $\forall j \neq k$, we will consider $\rho(\mathbf{x}_{r,j}, \mathbf{x}_{t,k}) = 0$ if $|r-t| > t_{window}$.

In a single target scenario, the authors in [10] propose to use a sequential Monte-Carlo method, known as particle filter, in order to infer the single target characteristics given the observations. However, this method suffers from intrinsic limitations in high-dimensional systems [11]. In order to obtain a more efficient algorithm for multiple target tracking, we thus propose an alternative based on a more advanced methodology known as Sequential Markov Chain Monte Carlo [14].

3.2. Proposed SMCMC algorithm

Traditionally, Markov chain Monte Carlo (MCMC) methods are used to draw samples from probability distributions in a non-sequential setting. The advantages of MCMC over Importance Sampling (IS, which is the main principle used in particle filters) are that it is generally more effective in high-dimensional systems, and also easier to design for complex distributions. Recently, sequential MCMC schemes were proposed in the literature - see [14] for a review. The sequential MCMC (SMCMC) is a powerful sequential methodology for filtering that targets the joint posterior distribution defined in our case by Eq. (4). A MCMC procedure is used to make inference from this complex distribution. However, since we do not have a closed form representation of the posterior distribution $p(\mathbf{x}_{1:t-1,1:N}|y^{1:M}_{1:t-1,1:N})$ at time $t-1$, it will be approximated by an empirical distribution based on the current particle set:

$$p(\mathbf{x}_{1:t-1,1:N}|y^{1:M}_{1:t-1,1:N}) \approx \frac{1}{N_p}\sum_{j=1}^{N_p}\delta_{\mathbf{x}^{(j)}_{1:t-1,1:N}}(\mathbf{x}_{1:t-1,1:N}) \quad (7)$$

where N_p is the number of particles and (j) the particle index. Then, by plugging this particle approximation into Eq. (4),

$$\begin{aligned} p(\mathbf{x}_{1:t,1:N}|y^{1:M}_{1:t,1:N}) \propto \frac{1}{N_p}\prod_{i=1}^{M} p(y^i_{t,1:N}|y^i_{1:t-1,1:N}, \mathbf{x}_{1:t,1:N}) \\ \times \sum_{j=1}^{N_p} p(\mathbf{x}_{t,1:N}|\mathbf{x}^{(j)}_{t-1,1:N})\delta_{\mathbf{x}^{(j)}_{1:t-1,1:N}}(\mathbf{x}_{1:t-1,1:N}) \end{aligned} \quad (8)$$

Then, having made many joint draws from Eq. (8) using an appropriate MCMC scheme, the converged MCMC output for variable $\mathbf{x}_{1:t,1:N}$ can be extracted to give an updated particle approximation of $p(\mathbf{x}_{1:t,1:N}|y^{1:M}_{1:t,1:N})$ to be used at next time iteration. More specifically, after a burn-in period of N_{burn} , keep every MCMC output $\mathbf{x}^{(j)}_k = \mathbf{x}^n_k$ as the new particle set for the posterior distribution. In this way, sequential inference can be achieved. At time t and at the n-th MCMC iteration, the following procedure is performed to obtain samples from $p(\mathbf{x}_{1:t,1:N}|y^{1:M}_{1:t,1:N})$:

- Make a joint draw for $\mathbf{x}_{1:t,1:N}$ using a Metropolis-Hastings step,
- Refine the hidden state at current time t, $\mathbf{x}_{t,1:N}$, using a series of Metropolis-Hastings-within-Gibbs steps.

It should be noted that several sampling strategies in the refinement step can be done in order to improve the algorithm. In this paper, we sample successively each of the individual targets using a series of Metropolis-within Gibbs steps. The complete proposed algorithm is summarized in Algo. 1.

Following the acquisition of this non burn-in set of particles asymptotically drawn according to the density $p(\mathbf{x}_{1:t,1:N}|y^{1:M}_{1:t,1:N})$, the target state estimation at time t can be performed using the minimum mean square error citerion as the mean of the particles, which corresponds to the empirical approximation of the expectation of the marginalized posterior density $p(\mathbf{x}_{t,1:N}|y^{1:M}_{1:t,1:N})$:

$$\begin{aligned} \hat{\mathbf{x}}_{t,1:N} &= \int \mathbf{x}_{t,1:N} p(\mathbf{x}_{t,1:N}|y^{1:M}_{1:t,1:N}) d\mathbf{x}_{t,1:N} \\ &\approx \frac{1}{N_p}\sum_{j=1}^{N_p}\mathbf{x}^{(j)}_{t,1:N} \end{aligned} \quad (9)$$

4. SIMULATION RESULTS

In order to illustrate the performance of the proposed solution, we assume that each target evolves independently from the others in a field of 16 sensors as illustrated in Fig. 1, according to a Near Constant Velocity model [15, 16] which is defined as follows for the j-th target:

$$\mathbf{x}_{t,j} = \mathbf{F}_t\mathbf{x}_{t-1,j} + \mathbf{u}_{t,j} \quad (11)$$

where $\mathbf{F}_t$ would be a 4×4 transition matrix and $\mathbf{u}_{t,j}$ a vector of independent realizations of $\mathcal{N}(\mathbf{0}_4, \mathbf{Q}_t)$ with $\mathbf{Q}_t$ a 4×4 state noise covariance matrix, both $\mathbf{F}_t$ and $\mathbf{Q}_t$ depending only on the time gap between t and $t-1$. Here $\mathbf{F}_t$ and $\mathbf{Q}_t$ are defined as:

$$\mathbf{F}_t = \begin{bmatrix}\mathbf{I}_2 & \tau_t\mathbf{I}_2 \\ \mathbf{0}_2 & \mathbf{I}_2\end{bmatrix}, \mathbf{Q}_t = \sigma_{target}\begin{bmatrix}(\tau_t^3/3)\mathbf{I}_2 & (\tau_t^2/2)\mathbf{I}_2 \\ (\tau_t^2/2)\mathbf{I}_2 & \tau_t\mathbf{I}_2\end{bmatrix} \quad (12)$$

with τ_t the delta of time between two time steps, which is chosen constant and equal to 1 second, and $\sigma^2_{target} = 10^{-2}$.

In order to assess the accuracy of the proposed solution, we compute the root mean square error (RMSE) between the estimations and the real positions of the target (the estimations of other variables such as velocities or accelerations are not taken into account), averaged on a number of Monte Carlo (MC) runs:

$$\text{RMSE}_t = \sqrt{\frac{1}{N_{MC}N}\sum_{j=1}^{N}\sum_{n=1}^{N_{MC}}\|\hat{\mathbf{x}}^n_{t,j} - \mathbf{x}_{t,j}\|} \quad (13)$$

where $\hat{\mathbf{x}}^n_{t,j}$ is the estimated state of the j-th target from the n-th MC run. The RMSE is also averaged on the different targets, in order to present an average tracking performance for a single target.

At time t, to compute the n-th SMCMC particle $\mathbf{x}_{t,1:N}^n$:

Joint Draw using Metropolis-Hastings

- Randomly select a joint trajectory particle $\tilde{\mathbf{x}}_{1:t-1,1:N}$ by sampling it from the empirical measure of $p(\mathbf{x}_{1:t-1,1:N}|y_{1:t-1,1:N}^{1:M})$ obtained at the previous time iteration:

$$\tilde{\mathbf{x}}_{1:t-1,1:N} \sim \frac{1}{N_p}\sum_{j=1}^{N_p}\delta_{\mathbf{x}_{1:t-1,1:N}^{(j)}}(\mathbf{x}_{1:t-1,1:N})$$

- Draw a random sample for the current t-th time step:

$$\tilde{\mathbf{x}}_{t,1:N} \sim p(\cdot|\tilde{\mathbf{x}}_{t-1,1:N})$$

- Calculate the acceptance ratio which compares the likelihood given $\tilde{\mathbf{x}}_{1:t,1:N}$ with the likelihood given $\mathbf{x}_{1:t,1:N}^{n-1}$ (which is the one from the previous iteration $n-1$):

$$\alpha = \min\left(1, \frac{\prod_{i=1}^{M} p(y_{t,1:N}^i|y_{1:t-1,1:N}^i, \tilde{\mathbf{x}}_{1:t,1:N})}{\prod_{i=1}^{M} p(y_{t,1:N}^i|y_{1:t-1,1:N}^i, \mathbf{x}_{1:t,1:N}^{n-1})}\right) \quad (10)$$

- Accept this proposed particle or reject it:
draw $a \sim \mathcal{U}[0,1]$
if $(a < \alpha)$ **then**
  accept the particle, thus $\mathbf{x}_{1:t,1:N}^n := \tilde{\mathbf{x}}_{1:t,1:N}$
else
  reject the particle, thus $\mathbf{x}_{1:t,1:N}^n := \mathbf{x}_{1:t,1:N}^{n-1}$
end

Refinement using Metropolis-within-Gibbs

- Successively sample each target:
for $b = 1$ **to** N **do**
  - Define $\tilde{\mathbf{x}}_{1:t,1:N} := \mathbf{x}_{1:t,1:N}^n$
  - Draw a new sample for the b-th target at current time t

$$\tilde{\mathbf{x}}_{t,b} \sim p(\cdot|\tilde{\mathbf{x}}_{t-1,b})$$

  - Calculate the acceptance ratio as in equation (10), with the modified particle $\tilde{\mathbf{x}}_{1:t,1:N}$.

  - Accept this proposal particle or reject it:
  draw $a \sim \mathcal{U}[0,1]$
  if $(a < \alpha)$ **then**
    accept the particle, $\mathbf{x}_{t,b}^n = \tilde{\mathbf{x}}_{t,b}$
  else
    reject the particle, do not update the b-th block in $\mathbf{x}_{t,1:N}^n$
  end
end

Output: Sample $\mathbf{x}_{1:t,1:N}^n$

Algorithm 1: Proposed SMCMC for multi-target tracking.

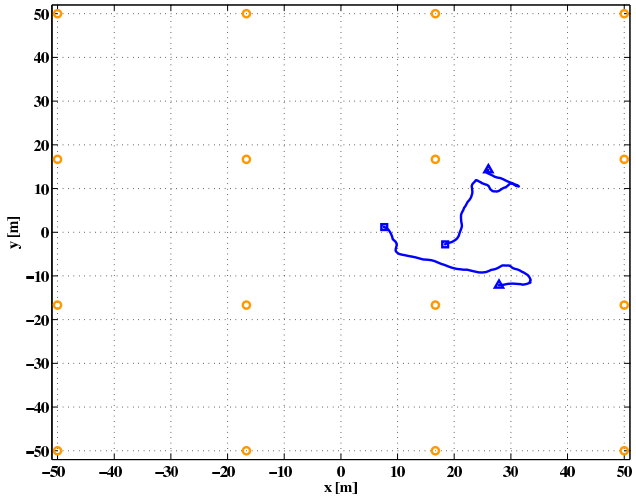

Fig. 1. Example of trajectories for 2 targets (in blue lines, □/△ represent the starting and stopping points) and 16 sensors (in orange circles), over 100 time steps (100 seconds).

4.1. Shadowing correlation performance improvements

In order for the assumption of independence between sensors to be acceptable, we use a decorrelation distance for the Gudmunson model of $D_c = 10$ meters, where the distance between sensors for a grid of $M = 16$ sensors is about 33 meters ; the trajectory scenario from Fig. 1 with $N = 2$ targets is used, and the SMCMC algorithm has $N_p = 500$ particles with a burn-in period of $N_{burn} = \frac{1}{10}N_p$.

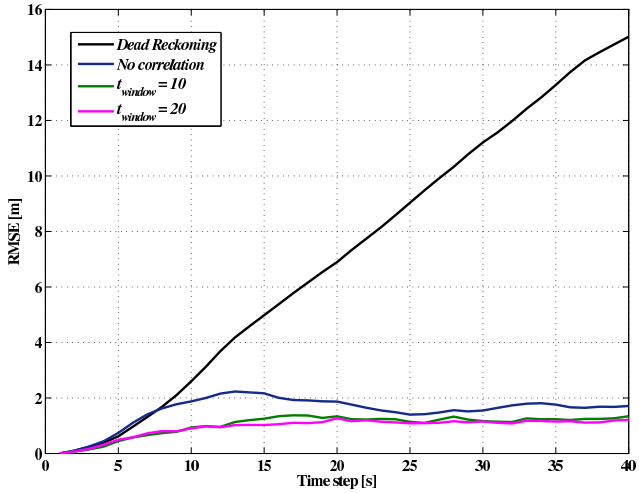

Fig. 2. Example of RMSE performance between a SMCMC algorithm without correlation and with correlation (with increasing time window). These algorithms are compared over the same set of observations for each MC run, in addition to being compared over the same set of target trajectories.

Fig. 2 shows the gain of performance induced by the use of spatio-temporal correlations, compared to no use of correlation at all, as well as the gain of performance for an increasing time window t_{window}. However, if the time window is increased too much, the estimation of the covariance matrix may become problematic as the

dimension of the state-space taken into account becomes too large. Simulations show that with large time windows, the RMSE may start diverging. Thus the time window should remain small, still allowing to benefit from the correlations between close time steps of a single target as well as different targets, but preventing the use of potentially strong correlations from far apart time steps between targets whose trajectories have crossed or ventured close to each other. However, the correlations between close time steps of a single target still remain the most important due to the proximity of the corresponding positions, at least in the type of scenarios considered here (it would no longer be true for instance for scenarios with very close targets, moving together, and a large delta of time between two measurements) ; a side-effect of this is the smallness of the performance improvement between $t_{window} = 10$ and $t_{window} = 20$, as most of the relevant correlation information is already taken into account with $t_{window} = 10$. Additionally and not surprisingly, the computational time increases with the time window ; thus an intermediate value is probably the best compromise overall.

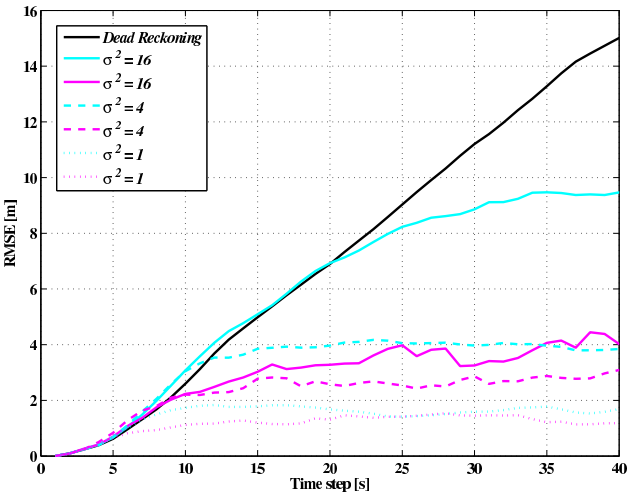

Fig. 3. Example of RMSE performance between algorithms with and without correlation, for different shadowing variances σ^2. The purple curves are with correlation, the cyan curves are without correlation.

Fig. 3 reveals how taking into account the correlation allows for greater performance improvements when the shadowing variance increases. Smaller noise implies more informative observations, thus diminishing the usefulness of additional information such as the correlation. The time window used for the correlated algorithm in this figure is $t_{window} = 10$.

4.2. SMCMC versus SIR

Now, we compare the proposed SMCMC algorithm with the particle filter that was proposed in [10] in a similar context for single target tracking. The particle filter used in this section is the Sequential Importance Resampling (SIR) [17] in which a resample move strategy after the resampling stage is employed in order to diversify the set of particles [18]. This strategy uses exactly the same step described as the refinement step in our proposed SMCMC and thus allows for a fair comparison between the two algorithms. Fig. 4 shows the RMSE obtained with both algorithms in which $N_p = 200$ particles are used to do the inference. In this simulation, the shadowing variance is $\sigma^2 = 1$, and different numbers of targets are used

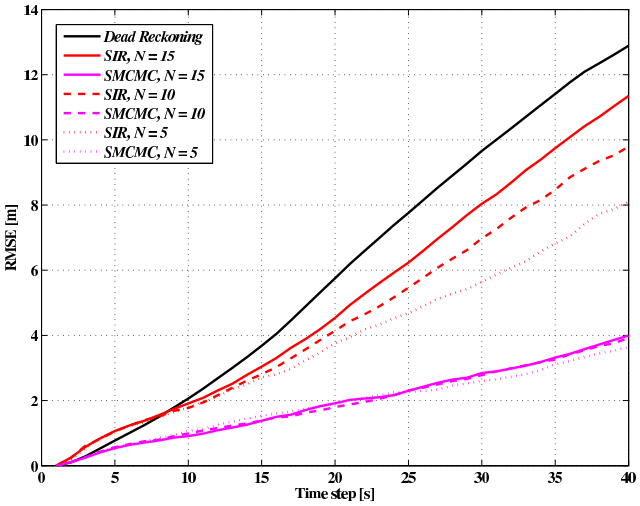

Fig. 4. SIR RMSE performance versus SMCMC RMSE performance for an increasing number of targets N.

($N = 5, 10, 15$). Indeed, the SIR algorithm's main weakness comes from the degeneration of the importance weights in situations where either the likelihood becomes too informative (with a too tight variance) and no longer covers the regions of the proposal distribution, or more interestingly in difficult situations where the state-space is high-dimensional. In these difficult high-dimensional scenarios, the results show the significant superiority of the proposed SMCMC against the SIR, with computational times of the same order.

5. CONCLUSIONS

In this paper, we have established that the use of spatio-temporal observation correlations, in the framework of Bayesian multiple target tracking based on RSS measurements, allows for significant performance improvements in difficult, very noisy scenarios. The implementation of a sliding time window, allowing to forget correlations from too old time steps, has illustrated how taking into account more information in the Bayesian process, thus with a greater time window, allows for gradually better performance ; although this does have drawbacks when the time window becomes too large. Finally, the overall superiority of the SMCMC approach over the SIR method for the complex problem of high-dimensional state-spaces was confirmed through appropriate simulations.

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