A MOBILE SYSTEM FOR NON-CENTRALIZED TARGET TRACKING IN PRESENCE OF DYNAMIC INTERFERENCES

Mónica F. Bugallo, Jonathan Beaudeau, and Petar M. Djurić

Department of Electrical and Computer Engineering
Stony Brook University
Stony Brook, NY 11794-2350
monica.bugallo@stonybrook.edu, JonBeaudeau@aol.com, petar.djuric@stonybrook.edu

ABSTRACT

This paper focuses on the application of particle filtering to tracking a single target by a network of mobile agents using measurements affected by dynamic interferences. The proposed solution is of general value and can be applied to systems with limited resources, and constraints on sensing modes, power and bandwidth utilization, and algorithm complexity. The highlight of the method is on its ability to handle multiple unknown dynamic sources of interference by compensation, which does not require prior information about the number of interferers, their locations, mobilities and powers, and does not attempt direct estimation of the number of interferers and their parameters and dynamics. The solution relies on a model that introduces a bias in the measurement equation that accounts for the interference contributions. We provide simulation results which demonstrate the performance of the proposed system.

***Index Terms*—** Mobile target tracking, particle filtering, interference compensation

1. INTRODUCTION

Target tracking by a network of mobile agents is of increased interest due to recent advances in the field of robotics [1]. This problem poses a different set of challenges than that of tracking with stationary sensor networks, and includes issues related to where and how the processing of the measurements of the sensors is carried out, along with who and how controls the movement of the mobile agents.

In a previous work, we addressed the problem of tracking with mobile agents where the agents are controlled by a central unit. The central unit is also in charge of processing the measurements made by each of the agents [2, 3]. The tracking at the central unit is carried out by applying particle filtering (PF) [4] or cost-reference PF [5, 6], which are methods especially suitable to address the problem given its nonlinear nature. We have also proposed a completely different strategy based on distributed processing [7]. There, each mobile agent processes all the available measurements and the agents make decisions without a central unit. These decisions include determining if the mobile agents should start tracking a new target, and if they start tracking, where they should move so that successful tracking of the target is maintained. Within this scheme, the agents that track the target collaborate by broadcasting their measurements to other agents that also track. Thus, each of the tracking agents have a complete set of measurements for estimating the state parameters of the target independently from one another. Note that here we adopt a completely different approach of cooperation among the agents compared to other recent efforts where the underlying principle is achieving a consensus [8].

In this paper, we extend the work in [7] and include in the measurement model an additive bias that accounts for dynamic interferers present in the surveyed area. We propose a method for target tracking in the presence of such biases based on PF [9], which tracks the kinematics of the target by using a discrete measure composed of particles and weights associated to the particles. We model the biases as dynamic parameters, which are treated as nuisance parameters since they are linear in the measurement equation, and therefore can be integrated out. In other words, we apply the concept of Rao-Blackwellization (RB) [10], which allows for improved estimation accuracy of the remaining unknowns in the model. A detailed description of the implementation of RB in the context of PF can be found in [11]. Some previous work on estimation in presence of biased measurements was presented in [12] where possible applications with solutions were provided. Additive and multiplicative biases were studied in [13] for detection of sensor faults in helicopters. In [14], the bias problem was addressed in the context of sensor networks. There it was suggested that the estimation of the states could be decoupled from the estimation of the biases and sequential estimation of the unknown states was accomplished by bias compensation. We have also investigated the problem of bias in target tracking, more specifically, in the context of bearings-only tracking with measurements that have additive

This work was supported by NSF under Awards CCF-0953316 and CCF-1018323.

bias [15]. The proposed method was based on PF and RB, and it employed only one Kalman filter (KF) instead of as many KFs as there are particles. An extension of this work was presented in [16, 17]. In all our previous contributions, the common feature is that the biases were considered as constant parameters. By contrast, in this paper, we address the problem of biased measurements where the biases are time varying with unknown dynamics. We prescribe a specific model for the biases which attempts to capture the variability of the biases with time. The model allows for a simple and relatively resource-efficient approach to handling multiple sources of additive dynamic interference without the necessity of individualized interference source localization.

The remainder of the paper is organized as follows. The next section introduces the problem of target tracking based on received signal strength (RSS) measurements, which may be corrupted by the presence of static or dynamic interferers. We propose a general model that accounts for all of the interferences and choose a simplified form for the RSS measurements to emphasize the intent of the paper. In Section 3, we describe an efficient algorithm which combines the use of PF and KF. Simulation results demonstrating performance of the model and method are presented in Section 4. Conclusions are provided in Section 5.

2. PROBLEM FORMULATION

We consider an area-of-interest under surveillance by N mobile agents. Upon detection of a target, mobile agents dispatch and track as long as the target remains within this zone. Track initialization is performed in a non-centralized fashion according to a predefined protocol based on measurements acquired immediately upon detection, and is not discussed here. We assume that a target moves in a 2-D plane according to the Markovian model

$$\boldsymbol{x}_t = \boldsymbol{A}\boldsymbol{x}_{t-1} + \boldsymbol{B}\boldsymbol{u}_t, \tag{1}$$

where $\boldsymbol{x}_t$ is a state vector defined by

$$\boldsymbol{x}_t = [x_{1,t} \; x_{2,t} \; \dot{x}_{1,t} \; \dot{x}_{2,t}]^\top$$

with $x_{1,t}$ and $x_{2,t}$ being the coordinates of the target in the 2-D Cartesian coordinate system, and $\dot{x}_{1,t}$ and $\dot{x}_{2,t}$, the components of the target's velocity and $^\top$ denotes the matrix transpose operator. The symbol $\boldsymbol{A}$ is a known 4×4 matrix, defined by

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{I}_2 & T_s\boldsymbol{I}_2 \\ \boldsymbol{0}_2 & \boldsymbol{I}_2 \end{bmatrix},$$

where T_s is the sampling period, and $\boldsymbol{I}_2$ and $\boldsymbol{0}_2$ are the identity and zero 2×2 matrices, respectively. The symbol $\boldsymbol{B}$ is a 4×2 known matrix given by

$$\boldsymbol{B} = \begin{bmatrix} \frac{T_s^2}{2}\boldsymbol{I}_2 \\ T_s\boldsymbol{I}_2 \end{bmatrix}.$$

The state noise is represented by the 2×1 vector $\boldsymbol{u}_t$ whose distribution is assumed to be Gaussian with zero mean and covariance matrix $\mathbf{C}_u$.

The agents that track the target are indexed by $n = 1, 2, \cdots, N$. They receive signals from the target that may be contaminated by the presence of dynamic interferences. The n-th agent collects an observation at time instant t, which is modeled by

$$y_{n,t} = h_{n,t}(\boldsymbol{x}_t) + b_{n,t} + v_{n,t}, \tag{2}$$

where, in general $h_{n,t}(\cdot)$ is a function that describes how the state of the target maps into a measured signal by the nth agent (in absence of observation noise), $b_{n,t}$ represents a time-varying additive bias affecting the agent's measurement and which is due to effects of unaccounted dynamic interferers at time instant t, and $v_{n,t}$ denotes the observation noise of the nth agent. The distribution of the noise is known, and in general, it does not have to be Gaussian.

For simplicity, here we assume that the function $h_{n,t}(\cdot)$ produces a scalar value and is given by

$$h_{n,t}(\boldsymbol{x}_t) = \frac{\Psi d_0^\alpha}{\|\boldsymbol{r}_{n,t} - \boldsymbol{l}_t\|^\alpha}, \tag{3}$$

where $\|\cdot\|$ denotes the Euclidean vector norm, $\boldsymbol{l}_t = [x_{1,t} \;\; x_{2,t}]^\top$ is the location of the target at time instant t; $\boldsymbol{r}_{n,t}$ is the location of the nth agent at time instant t, Ψ is the emitted signal power by the target measured at distance d_0, and α is a path-loss coefficient that depends on the transmission medium and is assumed known.

We model the bias as

$$b_{n,t} = b_{n,t-1} + |\sigma_t| g_{n,t} \tag{4}$$

where $g_{n,t}$ is a standard normal r.v. , $g_{n,t} \sim \mathcal{N}(0,1)$ and

$$\sigma_t = \sigma_{t-1} + e_t. \tag{5}$$

Thus, the *absolute value* of σ_t is the standard deviation of the bias. In expression (5), e_t denotes a perturbation that we model as a zero mean Gaussian random variable of known variance σ_e^2. The choice of a dynamic σ_t was made to account for nonstationarities in the bias arising from the unknown number and dynamics of the present interferers.

3. PROPOSED SOLUTION

In the PF framework, one seeks to obtain the posterior probability distribution of the state, $\boldsymbol{x}_t$, given the vector of sensors' measurements, $\boldsymbol{y}_t^\top = [y_{1,t} \;\; \cdots y_{N,t}]$, i.e., to obtain $p(\boldsymbol{x}_t|\boldsymbol{y}_{1:t})$ in the presence of the unknown biases $\boldsymbol{b}_t^\top = [b_{1,t} \;\; \cdots \;\; b_{N,t}]$. This is done by generating random measures composed of particles and associated weights and updating them recursively. In the problem of interest, we account for efficient estimation by processing the nonlinear unknowns using the particle filter and the conditionally linear ones (the biases of the observations) by use of Kalman filtering with as many KFs as particles [10].

Suppose that at time t we have the random measure of equally weighted particles,

$$\chi_t = \left\{\boldsymbol{x}_{0:t}^{(m)}, \sigma_{0:t}^{(m)}, w_t^{(m)}\right\}_{m=1}^{M} \tag{6}$$

with $w_t^{(m)} = \frac{1}{M}$ and M being the number of particles. We note that the weights are equal since at every step we perform resampling [9]. Assume also that at time instant t, the statistics of the biases are available and given by $\mathcal{N}(\widehat{\boldsymbol{b}}_t^{(m)}, \widehat{\mathbf{C}}_{b_t}^{(m)})$ with

$$\widehat{\boldsymbol{b}}_t^{(m)} = [\widehat{b}_{1,t}^{(m)}, \widehat{b}_{2,t}^{(m)}, \cdots, \widehat{b}_{N,t}^{(m)}]^\top, \tag{7}$$

$$\widehat{\mathbf{C}}_{b_t}^{(m)} = \mathrm{diag}\{\varsigma_{1,t}^{(m)}, \varsigma_{2,t}^{(m)}, \cdots, \varsigma_{N,t}^{(m)}\}. \tag{8}$$

The proposed algorithm proceeds as follows:

1. **Generation of particles.** Particles of the nonlinear unknowns are obtained from the prior densities as

$$\boldsymbol{x}_{t+1}^{(m)} \sim \mathcal{N}\big(\boldsymbol{A}\boldsymbol{x}_t^{(m)}, \mathbf{B}\mathbf{C}_u\boldsymbol{B}^\top\big), \tag{9}$$

$$\sigma_{t+1}^{(m)} \sim \mathcal{N}\big(\sigma_t^{(m)}, \sigma_e^2\big). \tag{10}$$

2. **Computation of weights**. The updating of the weights is done according to

$$\tilde{w}_{t+1}^{(m)} = \prod_{n=1}^{N} p\,(y_{n,t+1}\,|\,\boldsymbol{x}_{t+1}^{(m)}, \sigma_{t+1}^{(m)}), \tag{11}$$

where the distributions $p\,(y_{n,t+1}\,|\,\boldsymbol{x}_{t+1}^{(m)}, \sigma_{t+1}^{(m)})$ are Gaussians with respective means $E(y_{n,t+1}) = h_{n,t+1}(\boldsymbol{x}_{t+1}^{(m)}) + \widehat{b}_{n,t}^{(m)}$ and variances $q_{n,t+1}^{(m)}$, with $\widehat{b}_{n,t}^{(m)}$ representing the estimated bias of the nth agent. Both $\widehat{b}_{n,t}^{(m)}$ and $q_{n,t+1}^{(m)}$ are obtained by a KF as in step 4. The resulting weights are then normalized,

$$w_{t+1}^{(m)} = \tilde{w}_{t+1}^{(m)} / \sum_{k=1}^{M} \tilde{w}_{t+1}^{(k)}. \tag{12}$$

3. **Estimation of the nonlinear states.** A possible estimate of the parameters of interest is given by

$$\hat{\boldsymbol{x}}_{t+1} = \sum_{m=1}^{M} w_{t+1}^{(m)} \boldsymbol{x}_{t+1}^{(m)}, \tag{13}$$

$$\hat{\sigma}_{t+1} = \sum_{m=1}^{M} w_{t+1}^{(m)} \sigma_{t+1}^{(m)}. \tag{14}$$

4. **Measurement update of the linear states.** If we start with $b_{n,0} \sim \mathcal{N}(\mu_0, \varsigma_0)$ (the priors are the same for all streams and agents), then

$$\begin{aligned}\widehat{b}_{n,t+1}^{(m)} &= \widehat{b}_{n,t}^{(m)} + \frac{s_{n,t+1}^{(m)}}{q_{n,t+1}^{(m)}} \\ &\times \left(y_{n,t+1} - h_{n,t+1}(\boldsymbol{x}_{t+1}^{(m)}) - \widehat{b}_{n,t}^{(m)}\right),\end{aligned} \tag{15}$$

where

$$s_{n,t+1}^{(m)} = \varsigma_{n,t}^{(m)} + \sigma_{t+1}^{(m)^2}, \tag{16}$$

$$q_{n,t+1}^{(m)} = s_{n,t+1}^{(m)} + \sigma_v^2, \tag{17}$$

$$\varsigma_{n,t+1}^{(m)} = \frac{s_{n,t+1}^{(m)}\sigma_v^2}{q_{n,t+1}^{(m)}}. \tag{18}$$

5. **Resampling.** The resampling is performed using the updated weights $w_{t+1}^{(m)}$ [9].

Finally, note that the initialization of the algorithm is carried out by considering a prior corresponding to the target's initial state, i.e., $\boldsymbol{x}_0^{(m)} \sim \pi_0(\boldsymbol{x}_0)$; by assuming equal weights, i.e., $w_0^{(m)} = \frac{1}{M}$; and by setting the values of $\hat{\boldsymbol{b}}_0$ and $\hat{\mathbf{C}}_{b_0}$ as mentioned in Step 4.

4. COMPUTER SIMULATIONS

For the performance evaluation of the new interference compensation algorithm, we used a similar simulation scenario as in [7] . Nine sensors were initially distributed across a 3 x 3 grid. The target approached the sensor grid from a random location and subject to random perturbations. Once the target was within detection range of the grid, four of the sensors were assigned to track the target. The sensors maintained a distance of 3 m from the target. The number of particles for the PF algorithm was set to $M = 700$, whereas $\alpha = 2$, and $T = 1$. The state and observation noises were zero-mean Gaussian with variances $\sigma_u^2 = 0.0005$ and $\sigma_v^2 = 0.005$, respectively. Some time after the tracking stabilized ($t = 50$ s), the interfering biases were initialized. In our simulations, we evaluated the performance of the algorithm with biases that were "artificial" and behaved according to the described model, along with biases due to contributions of real interfering targets. Figure 1 shows a sample realization of the tracking error for modeled bias with a variance perturbation of $\sigma_e = 0.02$. It can be seen that the uncompensated "raw" filter (red) fails immediately after the bias is turned on, while there is an almost unnoticeable increase in the error over time for the compensated filter (black). The actual interference bias for the first sensor along with the corresponding estimates obtained by the proposed method are shown in Figure 2.

Figure 3 shows the mean square error (MSE) of the target position over 100 trials with several values of the model

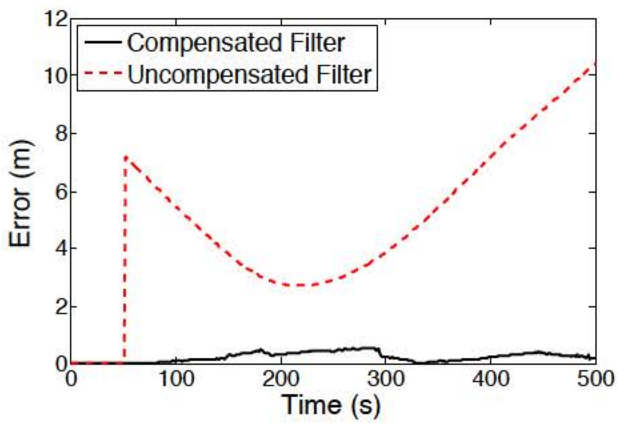

Fig. 1. Error for single realization with $\sigma_e = 0.02$.

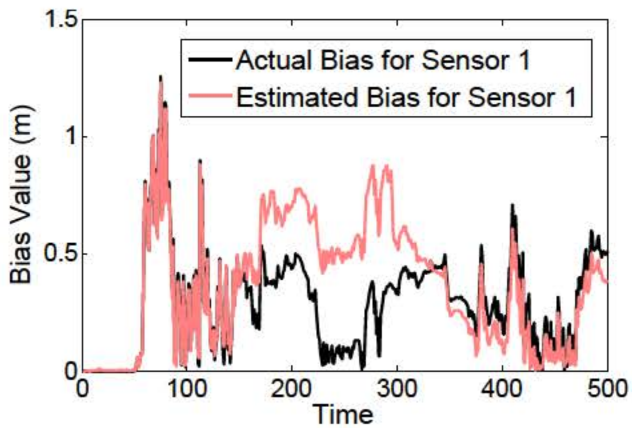

Fig. 2. Interference bias estimation with $\sigma_e = 0.02$.

parameter σ_e. Larger values of σ_e result in significant performance degradation over time that is expected as larger σ_e can result in larger values for the interference bias variance, subtracting from the target information present in the measurements.

The previous experiments revealed the performance of the compensated filter with the considered bias model. We next show the performance of the proposed filter in a more complex scenario where 10 interferers are deployed and allowed to randomly disperse. All interference sources are added to the received signal measurement in equation (2). To the best of our knowledge, there are no algorithms capable of maintaining acceptable tracking of the target in a setup with such large number of moving interferers without attempting to track each of the individual locations of the interferers. Figure 4 shows a single trajectory realization of this scenario. Note that the $\times$ marker indicates individual interference trajectories. As can be seen, tracking is maintained reasonably well by the proposed compensation algorithm for a considerable span of time.

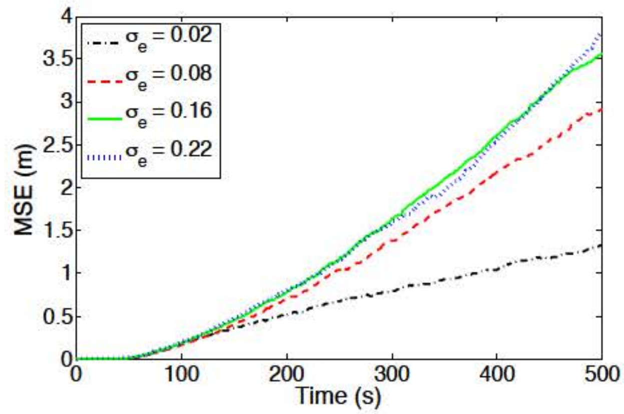

Fig. 3. MSE of the target position for various values of σ_e.

Figure 5 shows the MSE of the position of the target over 100 trials for the scenario with 10 interferers. Note the filter uses $\sigma_e = 2$ in the model; this value was found to yield best performance experimentally. In general, scenarios involving actual interference sources will not correspond to a specific value for σ_e. Future work will attempt to adapt σ_e of the filter based on the current "closest" model fit.

5. CONCLUSIONS

This paper discusses a PF technique for tracking a single target by a network of mobile agents using measurements affected by multiple additive dynamic interferers. The problem is formulated by lumping the net interference into an additive bias affecting sensor measurements. Assuming these biases are nuisance parameters and marginalizing them out, we propose an algorithm that combines a standard PF with Kalman filtering to efficiently resolve the tracking problem without localization of each interferer. Simulation results demonstrate successful tracking and reasonable performance for the proposed algorithm in cases where there is immediate failure of the non-compensated PF. Nonetheless, there is a steady accumulation of tracking error due to the added uncertainty from the biases. Additionally, the tracking performance is sensitive to deviations of the target movement from its expected track. As the interference bias variance grows, these deviations are "masked" as ambiguity in the biased sensor measurements. Thus, the ratio of signal power to bias variance can be interpreted as a signal-to-noise-ratio and it is expected that a noise threshold exists above which any tracking algorithm of this nature will fail. Future work will aim to further robustify the model and the proposed PF algorithm along with a possible method to quantify fundamental performance limits.

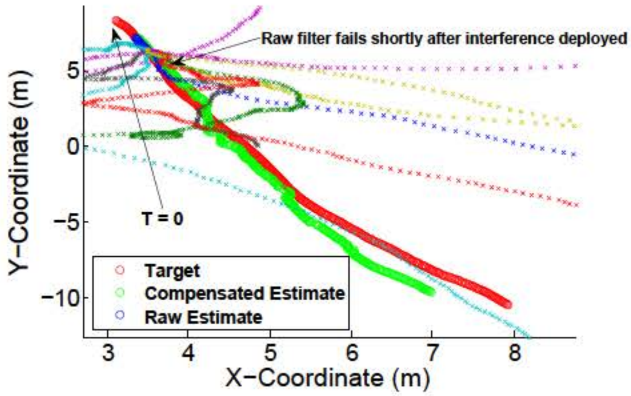

Fig. 4. Tracking with ten interfering sources deployed from the target with filter.

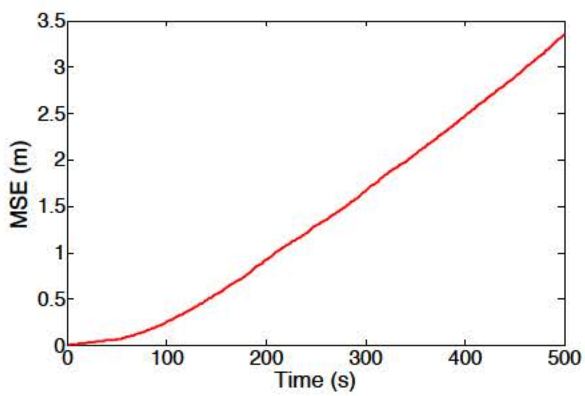

Fig. 5. MSE of the target position in a setup with 10 interference sources.

6. REFERENCES

[1] K. Dantu, M. Rahimi, H. Shah, S. Babeland, A. Dhariwal, and G. S. Sukhatme. Robomote: Enabling mobility in sensor networks. In *the Proceedings of the 4th International Symposium on Information Processing in Sensor Networks (IPSN)*, 2005.

[2] Y. Li and P. M. Djurić. Particle filtering for target tracking with mobile sensors. In *the Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, 2007.

[3] Y. Li and P. M. Djurić. Target tracking with mobile sensors using cost-reference particle filtering. In *the Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, 2008.

[4] P. M. Djurić and M. F. Bugallo. *Adaptive Signal Processing: Next Generation Solutions*, chapter Particle filtering, pages 271–331. Wiley Online Library, 2010.

[5] J. Míguez, M. F. Bugallo, and P. M. Djurić. A new class of particle filters for random dynamical systems with unknown statistics. *EURASIP Journal on Applied Signal Processing*, 2004(15):2278–2294, 2004.

[6] P. M. Djuric and M. F. Bugallo. Cost-reference particle filtering for dynamic systems with nonlinear and conditionally linear states. In *IEEE Nonlinear Statistical Signal Processing Workshop*, pages 183–188, 2006.

[7] P. M. Djurić, J. Beaudeau, and M. F. Bugallo. Non-centralized target tracking with mobile agents. In *the Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, 2011.

[8] R. Olfati-Saber, J. A. Fax, and R. M. Murray. Consensus and cooperation in networked multi-agent systems. *Proceedings of the IEEE*, 95(10):319–339, 2007.

[9] A. Doucet, N. de Freitas, and N. Gordon, editors. *Sequential Monte Carlo Methods in Practice*. Springer, New York, 2001.

[10] G. Casella and C. P. Robert. Rao-Blackwellization of sampling schemes. *Biometrika*, 83:81–94, 1996.

[11] T. Schon, F. Gustafsson, and P. Nordlund. Marginalized particle filters for mixed linear/nonlinear state-space models. *IEEE Transactions on Signal Processing*, 50(7):2279–2289, 2005.

[12] B. Friedland. Recursive filtering in the presence of biases with irreducible uncertainty. *IEEE Transactions on Automatic Control*, 21(5):789–790, 1976.

[13] G. Heredia, A. Ollero, R. Mahtani, M. Béjar, V. Remuss, and M. Musial. Detection of sensor faults in autonomous helicopters. In *Robotics and Automation, Proceedings of the 2005 IEEE International Conference on*, Barcelona, Spain, 2005.

[14] X. Lin and Y. Bar-Shalom. Multisensor target tracking performance with bias compensation. *IEEE Transactions on Aerospace and Electronic Systems*, 42:1139–1149, 2006.

[15] M. F. Bugallo, T. Lu, and P. M. Djurić. Fusion of information from biased sensor data by particle filtering. In *the Proceedings of the European Signal Processing Conference (EUSIPCO)*, 2007.

[16] M. F. Bugallo, T. Lu, and P. M. Djurić. Tracking with biased measurements of signal strength sensors. In *Proceedings of the 15th International Conference on Digital Signal Processing (DSP)*, 2007.

[17] M. F. Bugallo, T. Lu, and P. M. Djurić. Bearings-only tracking with biased measurements. In *the Proceedings of IEEE Workshop on Computational Advances in Multi-sensor Adaptive Processing (CAMSAP)*, 2007.