URSI GASS 2020, Rome, Italy, 29 August - 5 September 2020

Particle Filter based Approach for GNSS Interference Source Tracking: A Feasibility Study

Sanat K. Biswas*(1) and Ediz Cetin(2)
(1) IIIT Delhi, New Delhi, India, sanat@iiitd.ac.in
(2) Macquarie University, Sydney, NSW, Australia, ediz.cetin@mq.edu.au

Abstract

Global Navigation Satellite System (GNSS) signals are vulnerable to intentional or unintentional *Radio Frequency Interference* (RFI) sources. Since GNSS is used in numerous critical services, it is of interest to accurately localise and track the RFI source to take further actions. This paper explores the possibility of implementing the Particle Filter for localising a moving GNSS RFI source using *Angle of Arrival* (AOA) and *Time Difference of Arrival* (TDOA) observations. The performance of the Particle Filter and the *Single Propagation Unscented Kalman Filter* (SPUKF) are compared in this context in terms of estimation accuracy, the standard deviation in error and the processing time.

1 Introduction

Modern infrastructure and a plethora of services rely on the timing and positioning capabilities provided by the *Global Navigation Satellite Systems* (GNSS), in particular, the *Global Position System* (GPS). However, the low received power level makes the GNSS signals susceptible to *Radio Frequency Interference* (RFI) either from non-intentional or intentional sources [1, 2]. Hence, relatively weak RFI can jam GNSS signals and receivers, degrading or completely disrupting the functioning of the systems that rely on GNSS [3–5]. Therefore, GNSS itself has become a critical infrastructure which must be protected.

As the RFI source is unknown *a priori*, passive localization systems that typically use *Received Signal Strength* (RSS), source *Angle of Arrival* (AOA), *Time Difference of Arrival* (TDOA) or a combination of AOA/TDOA or *Frequency Difference of Arrival* (FDOA) to estimate the RFI position are needed [6]. One such system which combines AOA and TDOA processing to detect and localize RFI is the *GNSS Environmental Monitoring System* (GEMS) [7, 8], the precursor to the GRIFFIN system used in this paper.

Our initial work [9] looked at the performance of the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and the Single Propagation Unscented Kalman Filter (SPUKF) for RFI source geo-localization and tracking. It was observed that the SPUKF provides better performance in terms of estimation accuracy, confidence and processing time compared to the EKF, UKF and the snap-shot methods for a stationary RFI source or an RFI source moving at a constant speed. In this paper, we explore the possibility of using the Particle Filter for tracking a moving RFI source to obtain a higher estimation accuracy and confidence.

The paper is organised as follows: Section 2 provides a brief overview of the GRIFFIN system and describes the experimental setup. The Particle Filter is briefly described in Section 3. The system and observation model formulation are also provided. The performance of the Particle Filter for RFI source tracking is provided and compared with the SPUKF in Section 4. Conclusions and future work are given in Section 5

2 Experimental Setup

The GRIFFIN system consists of several spatially distributed *Sensor Nodes* (SNs), each incorporating a custom-designed multi-element circular antenna array, connected to a *Central Node* (CN) to quickly detect and geo-locate RFI(s) through hybrid AOA measurements at each SN and TDOA measurements between SNs. If an RFI is detected, the AOA to the RFI is established and each SN steers a beam at the RFI improving the *Signal-to-Noise Ratio* (SNR) in the proceeding TDOA processing at the CN, enhancing the accuracy over using the AOA and TDOA approaches independently.

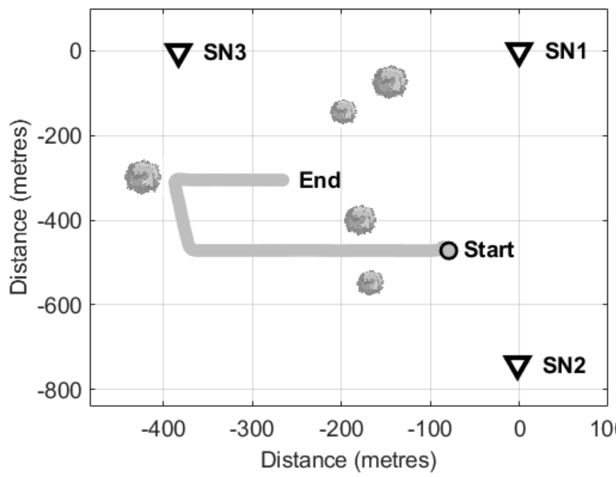

Figure 1. Field-trial Set-up

A network of three prototype GRIFFIN SNs, incorporating an 8-element antenna array, were spatially distributed across a $400 \times 800m$ area with system performance evaluated using various narrow- and wide-band interference sources as shown in Figure 1. The interference source power levels were set so as not to disrupt users outside the boundary of the trial area and GNSS monitoring stations were set-up at the perimeter to monitor the signal levels. In this work, we consider a dynamic RFI source, with the ground truth along with some of the trees shown in Figure 1. The ground truth data was obtained using a GNSS L1/L2-base station and a GPS RTK rover, and the locations of the SNs were surveyed prior to the field-trial allowing for a less ambiguous evaluation of the geo-localization performance that is being achieved.

3 Particle Filter Implementation

The Particle Filter is a recursive Bayesian Estimator which approximates the *Probability Density Function* (PDF) of a stochastic state vector using a set of a finite number of random sample state vectors [10]. A large number of samples are required to accurately represent the PDF. Each of the random sample state vectors is propagated to compute the *a priori* samples at the next observation epoch. The weight corresponding to each sample state vector is computed using a likelihood function corresponding to the observation(s) and the weighted average of the propagated samples are considered as the *a posteriori* mean state vector.

For implementing the Particle Filter for GNSS RFI source tracking problem, the AOA bias, clock bias and drifts between SNs are also estimated in addition to the position and velocity of the RFI source. Accordingly, the state vector for this estimation problem is defined as [9]:

$$\boldsymbol{X}(t) = \begin{bmatrix} \boldsymbol{r}^T & \boldsymbol{v}^T & \boldsymbol{b}_{\boldsymbol{T}}^T & \boldsymbol{d}_{\boldsymbol{T}}^T & \boldsymbol{b}_{\boldsymbol{a}}^T \end{bmatrix}^T \tag{1}$$

where

$$\boldsymbol{r} = \begin{bmatrix} x & y \end{bmatrix}^T \tag{2}$$

$$\boldsymbol{v} = \begin{bmatrix} \dot{x} & \dot{y} \end{bmatrix}^T \tag{3}$$

$$\boldsymbol{b}_{\boldsymbol{T}} = \begin{bmatrix} b_{T_{12}} & b_{T_{23}} & b_{T_{13}} \end{bmatrix}^T \tag{4}$$

$$\boldsymbol{d}_{\boldsymbol{T}} = \begin{bmatrix} d_{T_{12}} & d_{T_{23}} & d_{T_{13}} \end{bmatrix}^T \tag{5}$$

$$\boldsymbol{b}_{\boldsymbol{a}} = \begin{bmatrix} b_{a_1} & b_{a_2} & b_{a_3} \end{bmatrix}^T \tag{6}$$

Here, $\boldsymbol{r}$ and $\boldsymbol{v}$ are the position and velocity vectors of the RFI source, $b_{T_{ij}}$ is the clock bias and $d_{T_{ij}}$ is the clock drift respectively for the i^{th} and j^{th} sensor nodes and b_{a_i} is the AOA bias for the i^{th} sensor node. Considering the clock biases, drifts and AOA biases as constants, the dynamic model can be written as

$$\begin{bmatrix} \dot{\boldsymbol{r}} \\ \dot{\boldsymbol{v}} \\ \dot{\boldsymbol{b}}_{\boldsymbol{T}} \\ \dot{\boldsymbol{d}}_{\boldsymbol{T}} \\ \dot{\boldsymbol{b}}_{\boldsymbol{a}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}_{4\times4} & \boldsymbol{0}_{4\times9} \\ \boldsymbol{0}_{9\times4} & \boldsymbol{0}_{9\times9} \end{bmatrix} \begin{bmatrix} \boldsymbol{r} \\ \boldsymbol{v} \\ \boldsymbol{b}_{\boldsymbol{T}} \\ \boldsymbol{d}_{\boldsymbol{T}} \\ \boldsymbol{b}_{\boldsymbol{a}} \end{bmatrix} + \begin{bmatrix} \boldsymbol{0}_{2\times1} \\ \boldsymbol{a}_{2\times1} \\ \boldsymbol{0}_{9\times1} \end{bmatrix} + \boldsymbol{v}(t) \tag{7}$$

where

$$\boldsymbol{A}_{4\times4} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{8}$$

and $\boldsymbol{a}_{2\times1}$ is the unknown acceleration vector and $\boldsymbol{v}(t)$ is the process noise vector.

The AOA observation θ_i from the i^{th} node and the TDOA measurement δt_{ij} between the i^{th} and j^{th} sensor nodes at the k^{th} time instant can be expressed as

$$\theta_i(k) = tan^{-1}\left(\frac{x(k) - x_i}{y(k) - y_i}\right) + b_{a_i} + \eta_a(k) \tag{9}$$

$$\delta t_{ij}(k) = \frac{1}{c}\left(\|\boldsymbol{r}_i - \boldsymbol{r}(k)\| - \|\boldsymbol{r}_j - \boldsymbol{r}(k)\|\right) + b_{T_{ij}} + k d_{T_{ij}} + \eta_T(k) \tag{10}$$

where x_i and y_i are the x- and y-coordinate of the i^{th} sensor node, $\eta_a(k)$ is the AOA measurement noise, $\boldsymbol{r}_i$ and $\boldsymbol{r}_j$ are the position vectors of the i^{th} and j^{th} sensor nodes respectively and $\eta_T(k)$ is the TDOA measurement noise.

The PDF for the state vector is assumed Gaussian and accordingly, 2000 sample state vectors are drawn from the initial PDF assumption. Each of the 2000 samples was individually propagated by integrating equation (7). The weight corresponding to each sample was generated as per the sequential importance sampling algorithm [11] and in the case of degeneracy, re-sampling was performed [11].

4 Results and Discussion

Using the methodology described in section 3 the position of a moving GNSS RFI source was estimated using the Particle Filter. As mentioned earlier that the motivation for using the Particle Filter in this problem was to explore the possibility of improving the tracking performance for the case of moving RFI source. In the earlier work [9] it was observed that the SPUKF provides better performance in terms of accuracy, uncertainty and processing time for a GNSS RFI source localisation for the stationary case or when the RFI source is moving at a constant speed. Hence it is of interest to compare the performance of the SPUKF and the Particle Filter in this context.

Figure 2 shows the AOA and TDOA observations when the RFI source is moving at a constant speed along the x-axis. It can be observed that at some time instants the AOA and TDOA observations are unavailable due the obstructions.

The estimation errors and corresponding standard deviations along the x- and y-axis for the SPUKF is shown in Figure 3 [9]. It can be observed that the SPUKF provides the estimation solution with higher confidence than the snapshot i.e. Least Square method when the target is moving at a constant speed [9]. However, the SPUKF is unable to

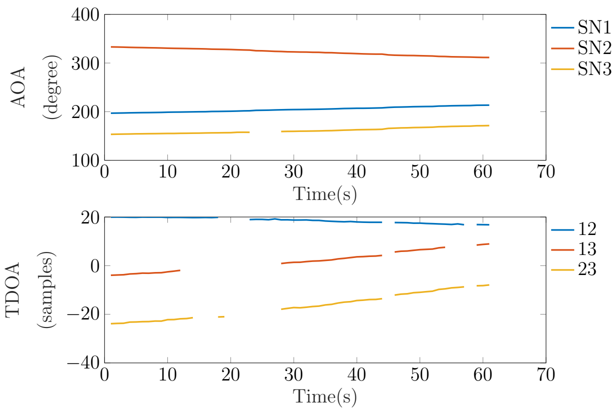

Figure 2. AOA and TDOA

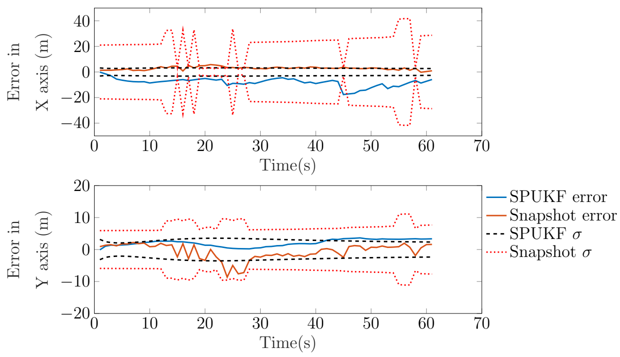

Figure 3. SPUKF error

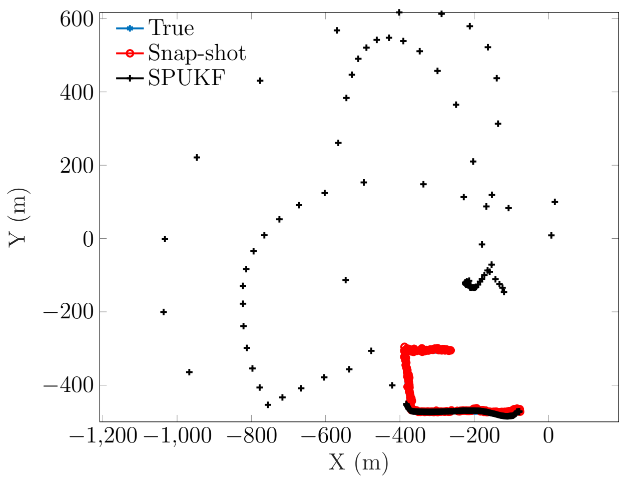

Figure 4. SPUKF X-Y position

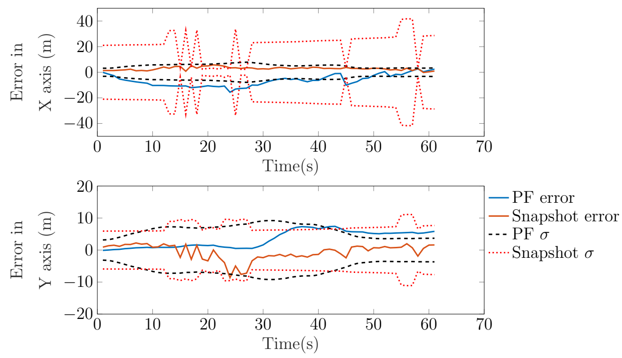

Figure 5. PF error

track the RFI source when the source starts accelerating. This can be observed in Figure 4.

The position estimation error and standard deviation for the Particle Filter algorithm are shown in Figure 5 when the RFI source is moving at a constant speed. It can be observed that the overall uncertainty in the solution is reduced due to the reduction in the standard deviation, compared to the snap-shot method.

The RFI source position estimated by the Particle Filter for the entire duration of the experiment is shown in Figure 6. One can conclude from Figures 4 and 6 that the Particle Filter solution is better than the SPUKF in terms of tracking performance. However, the Particle Filter solution is not as accurate as of the snap-shot method in terms of tracking the target, in this case. This is predominantly due to the unavailability of acceleration information in the system model.

The average estimation error, average standard deviation and the processing time per time step for the SPUKF and the Particle Filter are summarised in Table 1. It should be noted that the processing time for the Particle Filter is significantly higher than the SPUKF and it is anticipated that with an increased number of particles the processing time will increase further.

From the results presented above, it can be concluded that the traditional Particle Filter is not the most suitable solution to obtain a position estimation with higher confidence for the GNSS RFI source tracking. Additionally, the processing time is significantly higher than the SPUKF based solution. However, it is also observed that the Particle Filter based solution can reduce the solution standard deviation and hence increases the precision.

Table 1. SPUKF and Particle Filter comparison

	Average Error (m)	Average σ (m)	Processing time (ms)
SPUKF	8.359	4.152	6.195
Particle Filter	8.395	7.988	783.9

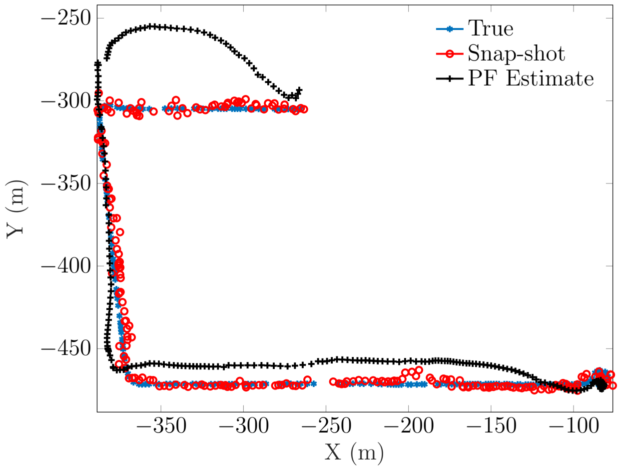

Figure 6. PF X-Y position

5 Conclusion

A Particle Filter based GNSS RFI source localisation is presented. It is observed that the Particle Filter based method improves upon the SPUKF method in terms of better tracking of the moving RFI source. However, the solution is not better compared to the snap-shot method, predominantly due to the unavailability of the target acceleration information to the system. Additionally, the Particle Filter approach requires significantly higher processing time. It is anticipated that a model-predictive approach can be utilised to estimate the source acceleration and the dynamic model can be updated accordingly at every time step in the Particle Filter to address the error due to the unavailability of the acceleration information. Further, the Extrapolated Single Propagation Technique [12] can be used in the Particle Filter to reduce the computation time significantly.

Acknowledgement

The authors would like to thank GPSat Systems Australia Pty. Ltd. for providing prototype GRIFFIN system field-data.

References

[1] H. Kuusniemi, E. Airos, M. Z. H. Bhuiyan, and T. Kröger, “GNSS jammers: How vulnerable are consumer grade satellite navigation receivers?,” *European Journal of Navigation*, vol. 10, no. 2, pp. 14–21, 2012.

[2] A. Jafarnia-Jahromi, A. Broumandan, S. Daneshmand, and G. Lachapelle, “Vulnerability analysis of civilian L1/E1 GNSS signals against different types of interference,” in *Proceedings of the 28th International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS+ 2015)*, (Tampa, Florida), pp. 3262–3271, Sept. 2015.

[3] J. W. Betz, “Effect of narrowband interference on GPS code tracking accuracy,” in *Proceedings of the 2000 National Technical Meeting of The Institute of Navigation*, (Anaheim, CA), pp. 16–27, Jan. 2000.

[4] A. Grant, P. Williams, N. Ward, and S. Basker, “GPS jamming and the impact on maritime navigation,” *Journal of Navigation*, vol. 62, p. 173–187, Apr. 2009.

[5] D. Borio, C. O’Driscoll, and J. Fortuny, “Jammer impact on Galileo and GPS receivers,” in *2013 International Conference on Localization and GNSS (ICL-GNSS)*, (Turin, Italy), pp. 1–6, June 2013.

[6] A. G. Dempster and E. Cetin, “Interference localization for satellite navigation systems,” *Proceedings of the IEEE*, vol. 104, pp. 1318–1326, Jun. 2016.

[7] E. Cetin, R. J. R. Thompson, and A. G. Dempster, “Passive interference localization within the GNSS environmental monitoring system (GEMS): TDOA aspects,” *GPS Solutions*, vol. 18, pp. 483–495, Oct. 2014.

[8] E. Cetin, R. J. R. Thompson, M. Trinkle, and A. G. Dempster, “Interference detection and localization within the GNSS environmental monitoring system (GEMS) – system update and latest field test results,” in *Proceedings of the 27th International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS+ 2014)*, (Tampa, Florida), pp. 3449–3460, Sept. 2014.

[9] S. K. Biswas and E. Cetin, “GNSS Interference Source Tracking using Kalman Filters,” in *Proceedings of IEEE/ION PLANS 2020*, (Portland, Oregon), Apr. 2020.

[10] N. Gordon, D. Salmond, and A. Smith, “Novel approach to nonlinear/non-Gaussian Bayesian state estimation,” *IEE Proceedings F Radar and Signal Processing*, vol. 140, no. 2, p. 107, 1993.

[11] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, “A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking,” *IEEE TRANSACTIONS ON SIGNAL PROCESSING*, vol. 50, no. 2, p. 15, 2002.

[12] S. K. Biswas and A. G. Dempster, “Approximating Sample State Vectors Using the ESPT for Computationally Efficient Particle Filtering,” *IEEE Transactions on Signal Processing*, vol. 67, pp. 1918–1928, Apr. 2019.