Aerospace Systems (2021) 4:67–74
https://doi.org/10.1007/s42401-020-00080-9

ORIGINAL PAPER

Adaptive filter based on Monte Carlo method to improve the non-linear target tracking in the radar system

Khaireddine Zarai[1] · Adnane Cherif[1]

Received: 9 October 2020 / Revised: 7 December 2020 / Accepted: 15 December 2020 / Published online: 14 January 2021

Abstract

This article deals with the problem of degraded tracking performance of a high non-linear target in a radar system, well known by the divergence phenomenon. In our study, we aim to improve the target state estimation to imitate the tracking scenario as well as avoid the last cited undesirable phenomenon, generated during the non-linear measurements filtering, once using extended KALMAN filter. To overcome this issue, we have implemented a new approach based on the adaptive Monte Carlo (AMC) algorithm to replace the traditional method as is known by the extended KALMAN filter (EKF). The obtained experimental results showed a challenging remediation. Where, the AMC converges towards the accurate state estimation. Thus, more efficient than extended KALMAN filter. The experimental results prove that the designed system meets the objectives set for AMC referring to an experimental database obtained by a radar system, using MATLAB software development framework.

Keywords Radar · AMC · Extended KALMAN filter · Tracking · High non-linear target

Abbreviations

EKF	Extended KALMAN filter
AMC	Adaptive Monte Carlo
SR	Systematic resampling
PF	Particle filter
R	Covariance matrix of measurement noise
Q	Covariance matrix of process noise
E	Entropy function
SIS	Sequential importance sampling
NP	Number of nonlinear measurements (particles)
PDF	The probability density function

1 Introduction

The most common radar systems tracking issues are related to the Doppler filtering, target size, the number of targets detected in each scan then the well-known issue of high non-linearity. The last one pose a filtering issue, harming the real-time tracking process.

On the other hand, the target reflected signals nature are non-stationary, non-Gaussian, inter-interfered due to the transmission channel nature as well as the target motion [1, 2]. Furthermore, the high non-linearity of each target poses a stochastic filtering problem according to SWIRLING models.

In the same axis, we found in the literature several nonlinear filtering techniques [3–10], such as the analytic KALMAN filter (KF), extended KALMAN filter (EKF) and the unscented KALMAN filter (UKF).Then, the numerical method based on the particle filter (PF).

Where, the KF was proposed by KALMAN and BUCY in 1964 as a solution to solve such problems when the target is linear, while the EKF is supposed as a relative solution for the non-linearity. Both filters use various recursive algorithms, but they are considered as limited methods today in the case of high nonlinearity.

In several target tracking scenarios [11–14], once the measurements from the ground or space base, considering a receiver antenna may have a long delay. Then the filter estimator leads to an incorrect variance distributions prediction, this divergence [6, 8, 13] is due to different kind combinations of non-Gaussian and nonlinear update measurements with different accuracies. Here comes the importance of

✉ Khaireddine Zarai
khaireddine.zarai@fst.utm.tn

Adnane Cherif
adnen2fr@yahoo.fr

[1] Department of Physics, Faculty of Sciences of Tunis, 2095 Tunis, Tunisia

recursive filters to merge the distribution measurements (distance and angle) and estimate real-time target state vectors.

- Problem statement

The main problem occurs when the target is highly nonlinear and depends on nonlinear update measurements. In this case, the conventional analytical filter based on KF as an EKF; it linearizes the nonlinear measurements around the current predicted state using Taylor series and ignores the higher order terms in some calculations costs. Even the EKF process becomes insufficient to complete the full linearization process since the non-linearity turns to be higher. Consequently, the divergence appearance phenomenon will make unsatisfactory gain/signal–noise ratio (SNR) to maintain the progression then achieve the posterior estimation law.

In this paper, we focus on high nonlinear target tracking problems. To solve the performance degradation well known by the divergence phenomenon as appeared once using EKF, we identified the source of divergence. To overpass this issue, we implement an adaptive Monte Carlo (AMC) algorithm based on the particle filter methods.

2 Related works

For non-linear target tracking and state estimation in a radar system, various methods have been investigated.

The majority of each approach has focused on nonlinear target tracking scenarios through nonlinear dynamic measurements. There are many nonlinear filtering techniques in [15] such as the analytical filter based on KF, EKF and the particle filter (PF).

In [16], a discrete–continuous energy minimization is proposed for multi target tracking to solve the tracking issue with range rate measurement.

Many other works, based on KF likewise Interacting Multiple Models-KALMAN filter (IMM-KF) has been suggested [17] to solve the tracking issue with range rate measurement. As well, in [18], authors have suggested a maneuvering target position and velocity tracking method, based on non-linear model.

Whereas, in [19] the posterior Cramer-Rao bound (PCRB) and interacting multiple model (IMM) methods for target tracking in the presence of specular multipath are proposed by Marcel Hernandez and Alfonso Farina. A multimodel has been developed based on EKF to avoid noncooperative target tracking issue in the presence of specular multipath.

From the other hand, to avoid the degradation performance issues by the glint noise, in [20] [Jungen Zhang; Hongbing Ji; Qikun Xue] have offered an improved particle filter called MARKOV Chain MONTE CARLO (MCMC) integrated EKF (MCMC–EKF).

The divergence phenomena were mentioned in [21–28] in which, several nonlinear filtering techniques are investigated like EKF and the UKF to address this problem.

In [24], Zhicheng Huo, Fengjun Qi; Guangxu Ren; Mingqian Wang presented a new approach to analyze the reason of divergence phenomenon for EKF based on the balloon height problem method. Unfortunately, the majority of these methods don't have effective solutions except in [25, 26, 28] the modified Particle filter Gain, Skewed KALMAN even the state transformation extended KALMAN filter (ST-EKF), to some extent they are considered as a relatively effective solution.

To avoid the divergence phenomenon engendered by the EKF in high nonlinear target tracking. Our main contribution is

- the development of a new approach based on particle filter that we called adaptive Monte Carlo (AMC) algorithm, to make tracking in high nonlinearity more efficient.

This paper is organized as follows; related works in Sect. 2. Section 3, presents the methods which have been used in tracking scenarios, experimental results are discussed in Sects. 4 and 5, finally, the conclusion and the future works are given in Sect. 6.

3 Methods

In this section, we theoretically compare two different target-tracking scenarios in radar system using two different methods. Firstly the well-known EKF and after that our newly proposed specific filter called AMC.

3.1 Extended KALMAN algorithm

The EKF is characterized by its nonlinearity treatment. This propriety explicates its wide use due to good estimation performance and implementation simplicity in many cases.

However, it has been shown from the literature that EKF converges to an incorrect solution in several object-tracking applications; once we use dynamic models or when measurement models are being highly non-linear state vector functions.

In discrete-time, the implemented equations propagate and update the estimated states. Measurements are based on diverse approximations [1, 3–5, 9, 12, 13] described by the subsequent EKF algorithm:

Initialization step

$$\widehat{X}_0 \leftarrow \overline{X}_0$$
$$P_0 \leftarrow Q_0$$

Loop: for

For k=1, 2, 3…do

Delay

$$\widehat{X}_{(k-1/k-1)} \leftarrow \widehat{X}_{(k/k)}$$
$$P_{(k-1/k-1)} \leftarrow P_{(k/k)}$$

Prediction step

The Second order linearization around the predicted state:

$$F_k \leftarrow \nabla f_k(\widehat{X}_{(k/k-1)})$$
$$X_{(k/k-1)} \leftarrow f_k(\widehat{X}_{(k/k-1)})$$
$$P_{(k/k-1)} = F_k P_{k-1} F_k^T + Q_k$$

Innovation step

$$Y_{(k/k-1)} \leftarrow F_k . \widehat{X}_{(k/k-1)}$$
$$S_k \leftarrow H_k P_{(k/k)} H_k^T + R_k$$

KALMAN Gain: The Signal noise ratio (SNR)

$$K_k = P_{(k/k-1)} . H_k^T + S_k$$

Correction and Estimation Step:

Second order linearization around the estimate:

$$H_{(k/k)} \leftarrow \nabla h_k(\widehat{X}_{(k/k-1)}$$

$$\widehat{X}_{(k/k)} \leftarrow \widehat{X}_{(k/k)} + (Y_k - \widehat{Y}_{(k/k-1)})$$

$$P_{(k/k)} \leftarrow P_{(k/k-1)} - K . H_k . P_{(k/k-1)}$$

Loop: end.

End.

3.2 E K F limitation: the divergence phenomenon dilemma

The EKF process is the state estimation projection $\hat{X}_k$ on the orthogonal basic measurement space constructed from the innovation data $Y_k - Y_{(k/k-1)}$. Similarly, as already shown in the above algorithm; it makes possible to optimize the maximum likelihood criterion.

We denote from the previous equations that the covariance matrix sequence $P_{k/k}, P_{k/k-1}$ and EKF gain Y_k represent an independent observation Y_k. As a result, we could pre-calculate it, which reduces the real time calculation cost, where f_k and h_k are non-linear functions. The optimal filter must linearize them around the predicted state $\hat{X}_{k-1}$ and the current state $\hat{X}_k$. Taylor series are used to obtain the first and the second order state and observation equations.

When the dynamic target is nonlinear which leads to a nonlinear update measurements, the EKF performs the linearization process. Here we underline that EKF is only efficiently used in weak non-linearity cases to get suitable results. Taylor series can perform this process using the h function which considerably reduces the nonlinearity around the current predicted state $X_{(k/k-1)}$ as well as ignores the higher order terms in calculating cost. The EKF linearization process becomes inadequate, especially when there are excessive nonlinear measurements and the computation time increases. As a consequence, it diverges during the remaining tracking period. Therefore, the divergence phenomenon comes into view along with the KALMAN gain K_k (SNR) which is not enough to maintain the posterior law $\widehat{X}_{(k/k)}$ estimation process.

To get rid of this trouble, we consider a new numerical approach based on AMC, to ensure that the filter converges to the target effective state.

3.3 New approach based on AMC algorithm

3.3.1 Theoretical comparison

Our new AMC method is developed for state estimation, especially when we are faced with high non-linear and further non-Gaussian dynamic models. The last cited method allows us to approximate the full distribution probability using Np random samples. Not only the mean and the covariance compared to the analytic filter based on EKF.

AMC algorithm uses the sequential resampling process to avoid the filter divergence scenario, particularly when using high non-linear models and non-Gaussian distributions. Further, the process needs sufficient probability under the observed region. Accordingly, it is necessary to provide a probabilistic interpretation through the following probabilistic interpolation:

$$I(f) = EP[f(X)/Y] = \int_{1}^{Np} f(X) \cdot P(X/Y), \quad (1)$$

where the empirical mean function is defined as follows:

$$I_{Np}(f) = \frac{1}{Np} \cdot \sum_{i=1}^{Np} f(X^i). \quad (2)$$

X^i represents the set of independent and identical random variables from 1 to Np. If the number of samples Np tends toward infinity, the filter converges to $E(X)$. Hence, we obtain an error*:*

$$\varepsilon = I_{Np}(f) - I(f) \approx 0. \quad (3)$$

Otherwise, the conventional filter could diverge in low distribution particle number. Where, appears clearly our contribution (AMC Algorithm) by calculating the effective sample size

$$\tilde{T}_{\mathrm{eff}} = \frac{1}{\sum_{i=1}^{Np} W_k^{i2}}. \quad (4)$$

Then, the entropy function

$$E = -\sum_{i=1}^{Np} W_k^i \cdot \log_2 W_k^i \quad (5)$$

and the optimal entropy function

$$E_{\mathrm{opt}} = \log_2 N_p \quad (6)$$

of N_p particles. Moreover, E and E_{opt} should be calculated and compared; if $E < E_{\mathrm{opt}}$ the sub-algorithm systematic resampling (SR) remedy the particle divergence.

3.3.2 The general adaptive Monte Carlo (AMC) algorithm

The following algorithm represents AMC with systematic resampling:

Initialization
 Loop: For i = 1…Np generate $X_0^i \sim p(X_0)$ with
 $W_0^i = \frac{1}{Np}$; $N_{Th} = 1$; $\varepsilon = 0$
 Loop: End
Generation of nonlinear measurements (particles) related to their weights
 Loop: for k=1…K to predict

- □ Particle propagation over time
 For i =1…Np
 Generate $X_K^i \sim q(X_k/X_{0:K}^i;\ Y_k)$
 End.
 Assign $T_{samp} = N_p$
 Assign $Y_{1:K}$
 Update of the importance weights and propagation In time:
 For i =1 …N_P calculate
 $\widetilde{W}_k^i = \widetilde{W}_{k-1}^i \cdot p(Y_k/X_{k-1}^i)$
 End.
 Summing weights
 $S = \sum_{i=1}^{Np} W_k^i$
 Normalization of weights of importance
 For i = 1…N_p
 Normalize : $W_k^i = \frac{\widetilde{W}_k^i}{S}$
 End
- Calculate the effective sample size:
 $\tilde{T}_{\mathrm{eff}} = \frac{1}{\sum_{i=1}^{Np} W_k^{i\,2}}$
- Calculation of Entropy: $E = -\sum_{i=1}^{Np} W_k^i \cdot \log_2 W_k^i$
- Calculation of optimal entropy: $E_{opt} = \log_2 N_p$
 If $T_{eff} < T_{samp}$ or $\varepsilon < \varepsilon_{opt}$ do
 Call for systematic resampling
 Else $p(X_{0:k}/Y_{1:k}) = \sum_{i=1}^{Np} W_k^i \cdot \delta(X_{0:k} - X_{0:k}^i)$
 End.
 End.

The AMC method uses an approach that generates independent samples according to q (X/Y) law (law of arbitrary sample distribution) to obtain the desired posterior density p (X/Y). This method, called sequential importance sampling (SIS) enhanced by a sub-algorithm to avoid filter divergence recently designed by systematic resampling (SR) [5–7, 10, 26, 27]. It offers much better performance from Gain / SNR point of view than the EKF.

4 Experimental results

In this section, MATLAB software is used to simulate two different data under different scenarios as mentioned in the theoretical part. Although, it has a certain practical interest in showing the contribution of AMC method compared to the E.K.F conventional method.

A different number of nonlinear measurements (NP) are generated to compare EKF performance (Algorithm A) to AMC (Algorithm B). We expect that AMC heals the divergence problem, offers an important Gain / SNR ratio, simple and efficient compared to EKF.

4.1 Simulation model

To estimate a non-linear state X of a target, we must use a non-linear and a non-stationary state-space model. Different scenarios have been simulated using EKF and AMC approach during a time interval. In this framework, we present the following non-stationary state-space model:

$$\begin{aligned} X(k+1) =& 0.5\times X + \left[25\times\frac{X(k)}{\left[(1+X)^2\right]}\right] \\ &+ 8\cos(1.2k) + \text{Process noise}, \\ Y(k) =& \frac{X(k)^2}{20} + \text{measurement noise}. \end{aligned} \tag{7}$$

The following Table 1 show the variables (Time and number of measurements) that will be used for both simulation scenarios.

4.2 Simulation using Extended KALMAN filter

First, we investigate the case of highly nonlinear target using the (Eq. 7) model written in the previous part. The EKF is used for both scenarios mentioned in Table 1.

4.2.1 Simulation of scenario A

NP = 2500 nonlinear measurements (particles) along 50 s.

Table 1 The two algorithms simulation variables

Variables	Definition	Values	
t_f	The simulation time interval in seconds	Scenario A	50 s
		Scenario B	100 s
NP	The number of particles generated in t_f (Nonlinear measurements)	Scenario A	2500
		Scenario B	5000

4.2.2 Simulation of scenario B

We simulate with $N_P = 5000$ particles and $T = 100$ s.

As shown in Fig. 1, we note that the green curve indicates that the particles which represent the target effective state have the same tendency with the black curve, which indicates the EKF response estimator; it converges to target effective state in a short time interval between 10 and 30 s. Although this may seem sufficient with an average of nonlinear measurements $N_P = 2500$. Contrarily to Fig. 2, we notice more particle losses for the green curve between [10–30 s], [45–58 s] and [85–93 s, the filter diverges in many sequences when the tracking period becomes 100 s and the number of nonlinear measurements NP is up to 5000.

4.3 AMC Filter performance comparison

Using the same model above (Eq. 7), in this part we look to improve the target state X estimation and avoid the filter divergence during the processing period [50–100 s] using AMC algorithm. In the same context, we have assigned different NP particles of the AMC algorithm as a nonlinear measurements as mentioned in Table 1.

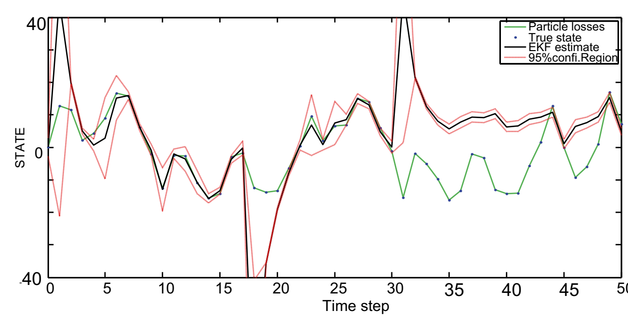

Fig. 1 Highly nonlinear target state estimation using NP = 2500 and $T = 50$ s

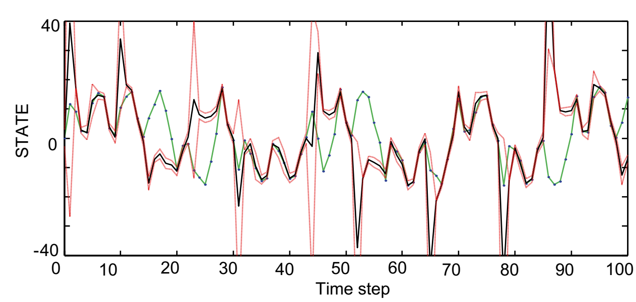

Fig. 2 Highly nonlinear target state estimation using NS = 5000 in $T = 100$ s

4.3.1 Simulation of scenario A

We simulate using NP = 2500 nonlinear measurements (particles) along $T = 50$ s.

4.3.2 Simulation of scenario B

We increase the number of nonlinear measurements to NP = 5000 and the time of estimation to $T = 100$ s.

4.3.3 Interpretation

According to Fig. 6, we notice that the probability density function shows a larger number of peaks and the obtained amplitude are up to 4000. Thus, providing more information about the target to be tracked through the ambiguity estimation process function. Contrarily, Fig. 4 shows a lower number of peaks with an amplitude less than 2000. On the other hand, the MAP estimation curve in Fig. 5 corresponds to the target state estimated over 100 s, which correlates with the particulate filter response. It gives a greater affinity for better estimation, especially when the number of nonlinear measurements (NP) increases to 5000.

5 Results discussion

5.1 Comparative study

The obtained results of scenario A and scenario B from both algorithms are compared and classified in the Table 2 hereunder.

5.2 Discussion

To strengthen the theoretical comparison in the previous section, we consider the obtained results in [22]. It is easily noticeable that under different circumstances we choose different filtering algorithms; either EKF or particle filter (PF).

In weak non-linearity tracking problem, the EKF is the best choice as found in relevant papers like in [13, 22, 23], while, having much less computational complexity compared to PF algorithm.

However, in our hypothesis, we are working on the highly nonlinear target tracking problem case with non-stationary white noise. It is clear from the results that the EKF's average ratio mean square error (RMSE) is much higher than the RMSE of AMC algorithm. Our new AMC method is more effective and gives minus divergence risk than EKF.

Therefore, it is important to develop a metric to gauge the non-linearity estimation problem.

In addition to RMSE, we have added the gain calculation/signal noise ratio (SNR), normalized root mean square error (NRMSE) and the probability density function (PDF) as a new metrics for more accurate results interpretation.

According to Table 2 results, the theoretical results are verified. The AMC algorithm is more efficient in case of high non-linear targets; when the number of nonlinear measurements NP = 2500 and NP = 5000 it gives us an important gain as the SNR is 13.9095 dB compared to EKF gain. The AMC have a low NRMSE between 0.1699 and 0.2018 which is sufficient to predict the effective target state and smooth his real trajectory. Contrarily, the EKF shows bad results; RMSE is up to 1.5842 when T2 becomes more than 100 s, low gain K_k/SNR is equal to − 3.99 dB as long as we raise the number of non-linear measurements.

Moreover, we conclude from Fig. 1 the EKF divergence after several measurement updates between 30 and 50 s due to the dynamic target which leads to a nonlinear update measurements. In Fig. 2, the EKF diverges in overtime contrarily to Figs. 3 and 5 the AMC shows that it converges to effective target state even if we increase the simulation time and/or the number of nonlinear measurements NP.

In Figs. 4 and 6, the density of probability function (PDF) is considered as a new metric to calculate the amplitude of each peak during the estimation period (Fig. 5). Indeed, an important number of peaks showed in Fig. 6 present the ambiguity function for effective target state estimation as evident remediation given by AMC approach.

In the light of this investigation, it is possible to conclude that our contribution has been verified. The new proposed AMC (algorithm B) estimates the state of higher number of non-linear targets more accurately than the EKF during a long period without performance degradation using a large number of nonlinear measurements (particles) up to 5000.

Table 2 Comparative results

	Algorithm A:EKF			Algorithm B:AMC		
	RMSE	NRMSE	SNR (dB)	RMSE	NRMSE	SNR (dB)
NP = 2500 $T1$(s) = 50	3.4512	0.4246	8.3730	2.3397	0.3856	9.3397
$T2$ (s) = 100 NP = 5000	15.4509	1.5842	-3.991	1.9866	0.2018	13.909

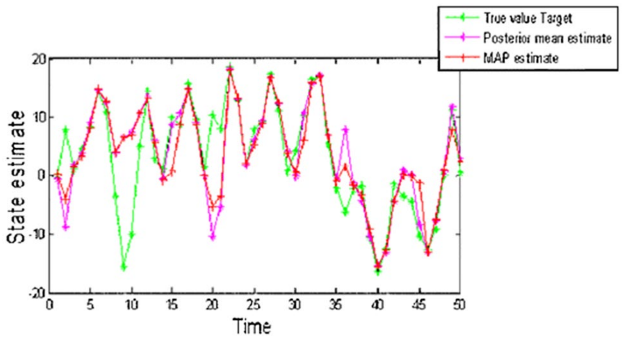

Fig. 3 Highly non-linear target state estimation using NP = 2500 in $T=50$ s

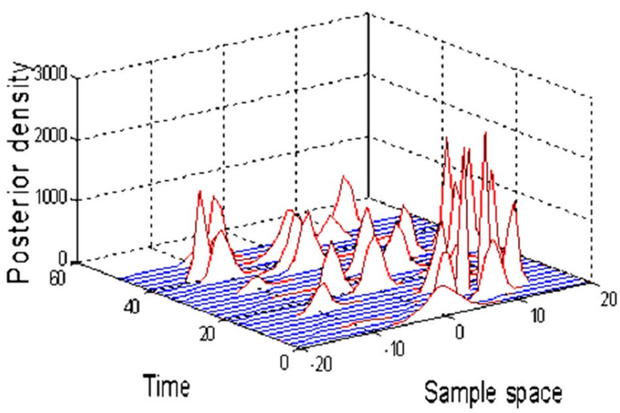

Fig. 4 The AMC posterior density function using NP = 2500 and $T=50$ s

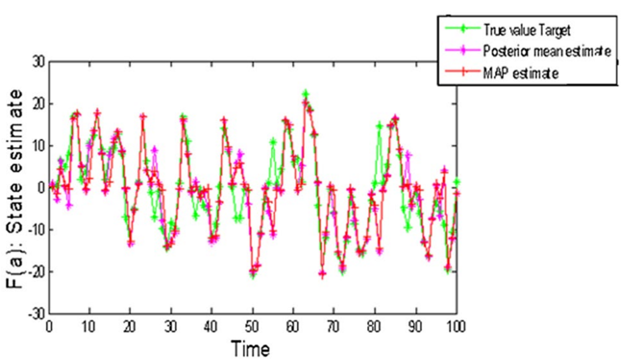

Fig. 5 Highly non-linear target state estimation using NP = 5000 in $T=100$ s

6 Conclusion and future works

In conclusion, in this paper, we presented a new approach to improve the non-linear target tracking as well as to avoid the filter divergence performances degradation.

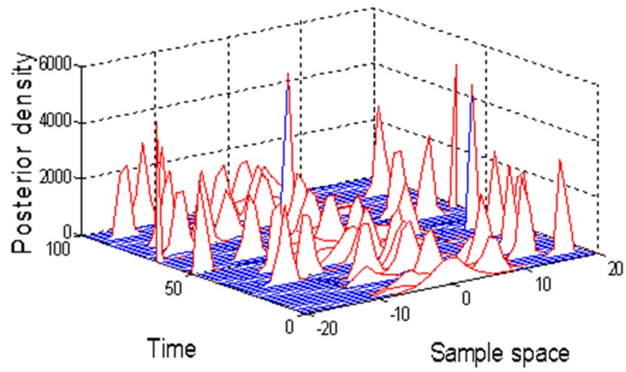

Fig. 6 The AMC posterior density function increasing NP to 5000 and T to 100 s

We overcame the constraints related to the high target nonlinearity modelling and avoid the filter divergence phenomenon. The experimental results validate what we mentioned in the theoretical part. The AMC approach is more efficient in complex cases which cannot be observed experimentally and even when simulated by EKF diverges to inappropriate results.

AMC has a fast calculation time and converges rapidly to its related effective states. Thus, it can be used in real-time tracking and in the presence of non-stationary white noise.

As well avoid the divergence phenomenon using the optimal entropy calculation likewise the sub-algorithm called systematic resampling (SR). It gives the necessary gain for the optimal filtering over a long period.

Then, finally we have undoubtedly increased the radar system performances using this new approach and we avoid the performance filter degradation. Even though having these persuasive results the method could be ameliorated by multiplying the number of targets. In our future research, we aim to implement this method aiming to enhance the multi targets tracking which compels us to add a data association filter to avoid the signal interference phenomenon.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Gennady K, Maria K (2016) The accurate continuous-discrete Extended Kalman filter for radar tracking. IEEE Trans Signal Process. https://doi.org/10.1109/TSP.2015.2493985
2. Wolff C (2009) Intrapulse modulation. Radartutorial. www.radartutorial.eu
3. Youngjoo K, Hyochoong B (2018) Introduction to Kalman Filter and its applications book. Kalman Filter. https://doi.org/10.5772/intechopen.80600

4. Boujemaa AEF, François D (2006) Kalman filtering in triplet markov chains François Desbouvrie. IEEE Trans Signal Process. https://doi.org/10.1109/TSP.2006.877651
5. Jean-Charles N, Gérard SJ (1997) Particle filtering of RADAR video signals for pointwise targets. Laboratory of analysis and architecture of CNRS systems, vol 14, no 1. International Information and Engineering Technology Association (IIETA)
6. Baoshuang G, Hai Z, Liuyang J, Zheng L, Maaz MB (2019) Adaptive unscented kalman filter for target tracking with unknown time-varying noise covariance. Sensors (Basel). https://doi.org/10.3390/s19061371
7. Blanc C, Trassoudaine L, Gallice J (2005) EKF and particle filter track-to-track fusion: a quantitative comparison from radar/LIDAR obstacle tracks. Int Conf Inform Fus. https://doi.org/10.1109/ICIF.2005.1592007
8. Hindawi Publishing Corporation (2014) A filtering algorithm for maneuvering target tracking based on smoothing spline fitting. Abstract and Applied Analysis. Hindawi Publishing Corporation, London (**Open access Article, 6 pages. ID 127643**)
9. Kim Y, Bang H (2018) Introduction to KALMAN filter and its applications. IntechOpen. https://doi.org/10.5772/intechopen.80600
10. Carine H, Jean-Pierre LC, Patrick P (2002) Sequential Monte Carlo methods for multiple target tracking and data fusion. IEEE Trans Signal Process. https://doi.org/10.1109/78.978386
11. Branko R, Sanjeev MA (2003) Tracking a manoeuvring target using angle-only measurements: algorithms and performance. Elsevier, Amsterdam, pp 1223–1238. https://doi.org/10.1016/S0165-1684(03)00042-2
12. Zhansheng D, Li XR, Chongzhao H, Hongyan Z (2020) Sequential unscented Kalman filter for radar target tracking with range rate measurements. IEEE. https://doi.org/10.1109/ICIF.2005.1591846
13. Perea L, How J, Elosegui P (2007) Nonlinearity in sensor fusion: divergence issues in EKF, modified truncated GSF, and UKF. Conf Paper. https://doi.org/10.2514/6.2007-6514
14. Kristine LB, Christopher JB, Graeme ES (2015) Cognitive radar framework for target detection and tracking. IEEE J Sel Top Signal Process. https://doi.org/10.1109/JSTSP.2015.2465304
15. Yanan L, Sese W, Zhuo S, Jihong S (2015) Evaluation of nonlinear filtering for radar data tracking. EURASIP J Wirel Commun Netw. https://doi.org/10.1186/s13638-015-0249-x
16. Anton M, Konrad S, Stefan R (2016) Multi-target tracking by discrete-continuous energy minimization. IEEE Tran Pattern Anal Mach Intell. https://doi.org/10.1109/TPAMI.2015.2505309
17. Yan-Chang L, Xian-Gang Z (2013) A Manoeuvring target tracking algorithm based on the interacting multiple models. Telkomnika 11(7):3997–4003. https://doi.org/10.11591/telkomnika.v11i7.2851
18. Saab Bofors Dynamics, Jarfalla S (2015) A constrained extended Kalman filter for target tracking. IEEE. https://doi.org/10.1155/2015/158570
19. Hernandez M, Farina A (2019) PCRB and IMM for target tracking in the presence of specular multipath. IEEE Trans Aerosp Electron Syst. https://doi.org/10.1109/TAES.2019.2948671
20. Zhang J, Ji H, Xue Q (2009) A new approach based on particle filter for target tracking with glint noise. IEEE Int Conf Radar Syst. https://doi.org/10.1109/ICSMC.2009.5346071
21. Lefebvre T, Bruyninckx H, Schuller JD (2002) A new method for the nonlinear transformation of means and covariances in filters and estimators. Autom Control IEEE Trans 47(8):1406–1409. https://doi.org/10.1109/TAC.2002.800742
22. Ruixin N, Varshney PK, Mark GA (2008) Curvature nonlinearity measure and filter divergence detector for nonlinear tracking problems. In : IEEE Explore, Conference Paper. INSPEC Accession Number: 10365880.
23. Yuming C, Wei L, Gaifang X, Hai Y, Ting X (2019) An improved strong tracking Kalman filter algorithm for the initial alignment of the shearer. Complexity. https://doi.org/10.1155/2019/3172501
24. Zhicheng H, Fengjun Q, Guangxu R, Mingqian W (2011) Research on divergence phenomenon and rejection method of Kalman filter on discrete system. IEEE. https://doi.org/10.1109/MACE.2011.5987709
25. Min-Hyun C, Min-Jea T (2017) Modified gain pseudo-measurement filter design for radar target tracking with range rate measurement. Mediterr Conf. https://doi.org/10.1109/MED.2017.7984280
26. Louis T, David G, Geordie R (2018) Monte Carlo methods and skewed Kalman filters for orbit estimation. Orbital ATK Conference Center, Washington
27. Alper A, Önder ME (2019) Multiple model Kalman and particle filters and applications: a survey. IFAC (International Federation of Automatic Control). Elsevier, Amsterdam. https://doi.org/10.1016/j.ifacol.2019.06.013
28. Wang M, Wenqi Wu, He X, Li Y, Pan X (2019) Consistent ST-EKF for long distance land vehicle navigation based on SINS/OD integration. IEEE Trans Veh Technol. https://doi.org/10.1109/TVT.2019.2939679