# Marginalized Particle Filter for Banana Problem in Long Range Radars

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***Abstract***

*Kalman filter and its variants are the most widely used state estimators for target tracking in radar systems. To satisfy linear Gaussian prerequisite of Kalman filter for optimal performance, target motion is usually modeled in Cartesian coordinates. Radar measurements which are in polar coordinates are either converted to Cartesian coordinates and applied to kalman filter in linear fashion called Converted Measurement Kalman Filter (CMKF) or directly applied in non-linear fashion as the Mixed Coordinates Filter (MCF) called Extended Kalman Filter (EKF). Nonlinear conversion process present in CMKF, creates banana shaped uncertainty region (non-Gaussian) in the 2D Cartesian coordinate, which creates bias & inconsistency in the converted measurement and it is more severe in long range targets. Linearization present in the EKF, leads to filter divergence. A recent study shows that for the banana problem, the Regularized Particle Filter (RPF) achieves better performance compared to CMKF and EKF approach. In the present work, Marginalized Particle Filter (MPF) is proposed for the banana problem, which is the combination of the particle filter and Kalman filter to reduce the computational complexity of RPF without compromising in performance.*

***Keywords—****Tracking, Nonlinear filtering, converted measurement, Banana Problem*

## I. INTRODUCTION

Detecting the presence of the target and estimating its dynamics (called tracking) using the noisy position measurement is the major functionality of any radar system. Detection confirms the presence or absence of the target, once targets are detected its dynamics needs to be estimated using a noisy radar measurement at regular intervals. Kalman filter and its variants are used extensively for estimation of target dynamics. The performance of the Kalman filter will be optimal only when state & measurement equations are linear and model & measurement noise are white Gaussian [1].

As shown in the Fig.1 Radar measures the position of the target in polar coordinate (Range and Azimuth or Bearing) w.r.t radar location. Target dynamics can be modelled either in Cartesian (Linear) or in polar (Non-Linear) coordinates. One approach is model the dynamics in Cartesian coordinate and radar measurements are converted from polar to Cartesian resulting in a Converted Measurement Kalman Filter (CMKF) [4],[5],[6],[7][16]. This nonlinear coordinate conversion introduces the nonGaussianity in the measurement noise which is the violation of the Kalman filter prerequisite. Compared to nonlinearity of dynamics in polar coordinates, measurement conversion introduces less nonlinearity and it is negligible in near ranges. Another approach is to use an Extended Kalman filter (EKF) [4], which includes the original measurements in a nonlinear fashion into the target state estimation, resulting in a mixed coordinate filter.

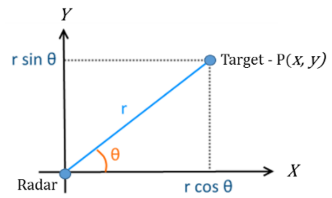



Fig.1, Coordinate System-2D

Standard measurement conversion equations

$$x = r\ \cos\theta \tag{1}$$

$$y = r\ \sin\theta \tag{2}$$

If the conversion process is unbiased, the performance of a converted measurement Kalman filter is superior to a mixed coordinate EKF [4]. Proposed approaches for conversion include the conventional conversion, the Unbiased Converted Measurement (UCM) and the Modified Unbiased Converted Measurement (MUCM). Recently proposed decorrelated version of the UCM technique (DUCM) address both the conversion and estimation bias[2].

The mixed coordinate filter EKF is the traditional and most widely used nonlinear filter in real world radar tracking systems [1]. In this algorithm, the measurement model is linearized around the predicted state estimate. The EKF has the advantage of being easily implementable with less computational requirements compared to particle filter. However, EKF may become unstable and sensitive to track initialization. Recently a modified version of EKF called MCAEKF [10],[11] which overcomes the stability problem by sacrificing the range accuracy during early stage of filtering. Particle filters are the most appropriate state estimator for the nonlinear and nonGaussian estimation problems. For the banana problem, the Regularized Particle Filter (RPF) achieves better performance compared to CMKF and EKF approach [11].

The paper is organized as follows. Problem definition and limitations of basic filters are described in Section II. Section III describes various converted measurement Kalman filters developed for the above problem and its limitations. Section IV describes the Mixed Coordinate Filters and its limitations. Section V presents basics of particle filter and its limitations and results of RPF for banana problem. Section VI explains about the proposed Marginalized Particle Filter(MPF) approach for banana problem. Simulations results for long target scenarios are presented in Section VII. Conclusions are presented in Section VIII.

## II. PROBLEM DEFINITION AND LIMITATIONS OF BASIC FILTERS

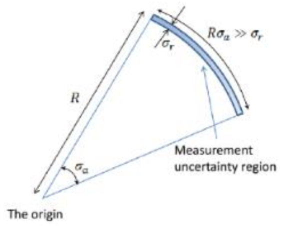
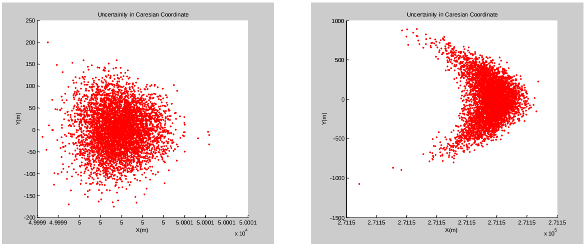
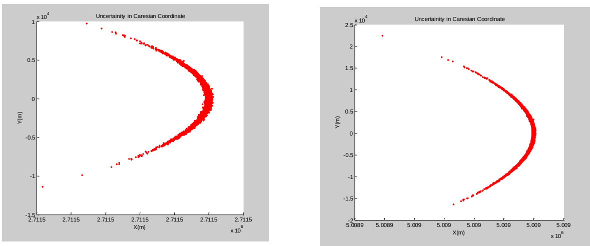



Fig.2, A curved measurement uncertainty region which is very accurate in the range direction, however has large uncertainty in the cross-range.



(a) At 50 km Range (b) At 271 km Range



(c) 2711 km Range (d) 5009 km Range

Fig.3, Polar to Cartesian coordinate conversion at various ranges for 0 deg azimuth, $\sigma_r$ = 0.2 m and $\sigma_a$ = 2 mrad.

The long-range tracking scenario presents an interesting challenge known as the banana (or crescent) problem in two dimensions [3] as in the Fig.2. As the range increases, the measurement uncertainty region takes a curved shape like a banana which is increasingly nonGaussian (non-elliptical) in the Cartesian coordinates. Polar to Cartesian coordinate conversion at various ranges are shown in Fig.3. Gaussian uncertainty in polar becomes nonGaussian in Cartesian due to nonlinear conversion equation and it is more visible in long ranges. This problem arises when the measurements are accurate in range and inaccurate in cross-range. As the range to a target becomes very large, even decent angular standard deviations can translate to severe inaccuracies in the cross range. This can result in degraded track accuracy and inconsistency (actual errors not commensurate with the filter-calculated covariance) in various filters.

Consider a 2-D tracking scenario in Fig.1 where the radar measures range 'r' and azimuth 'a' of a target. The target follows the continuous white noise acceleration (CWNA) motion model [11] with process noise intensity (PSD) $\tilde{q}$. The state of the target is defined as

$$X = [\,x \quad \dot{x} \quad y \quad \dot{y}\,]' \tag{3}$$

which evolves as

$$X(k+1) = FX(k) + V(k) \tag{4}$$

where T is the sampling time and transition matrix

$$F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

The covariance of the process noise in (4) is

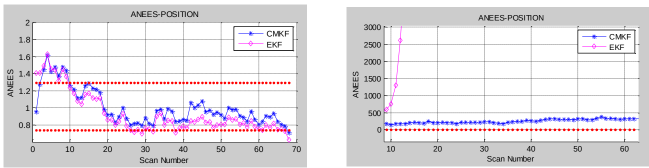
$$E[v(k)v(k)'] = \begin{bmatrix} \frac{1}{3}T^3 & \frac{1}{2}T^2 & 0 & 0 \\ \frac{1}{2}T^2 & T & 0 & 0 \\ 0 & 0 & \frac{1}{3}T^3 & \frac{1}{2}T^2 \\ 0 & 0 & \frac{1}{2}T^2 & T \end{bmatrix} \tilde{q} \tag{6}$$

The nonlinear measurements functions are given by

$$r = \sqrt{(x^2 + y^2)} + w_r \tag{7}$$

$$a = \arctan\left(\frac{y}{x}\right) + w_a \tag{8}$$

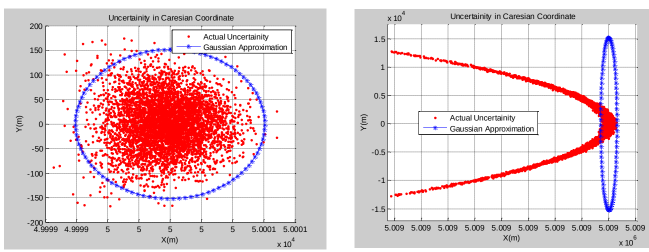
The measurement noises $w_r$ and $w_a$ are assumed to be zero mean white Gaussian with standard deviations $\sigma_r$ and $\sigma_a$ respectively. Assume that the sensor is at the origin which takes measurements of the target at every T=1sec, with measurement accuracy $\sigma_r$ = 0.2 m and $\sigma_a$ = 2 mrad. The target has process noise intensity $\tilde{q} = 10^{-3}$ m$^2$/s$^3$.




(a) Short Range (50 km) (b) Long Range (2711 km)

Fig.4, Evaluation of Average Normalized Estimation Error Square (ANEES) for conventional CMKF and EKF to check covariance consistency

From the Fig.4, in sort range both approaches i.e converted measurement approach and mixed coordinate approach are consistent and performs equally. But as the range increases EKF becomes unstable, though CMKF is stable still filter calculated covariance is much lower than the actual one. Though the actual uncertainty is a curved shape like a banana which is increasingly nonGaussian, both the filters approximate it as a Gaussian ellipse as shown in the Fig.5 (a) & Fig.5(b). Overlap between the actual and approximated uncertainty decreases as the range increases and filter becomes inconsistent.




(a) Short Range (b) Long Range

Fig.5 Measurement uncertainty and Gaussian approximation by basic filters in Cartesian coordinate

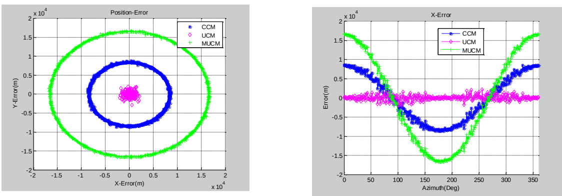
From the above results, for the general banana problem, the standard CMKF and EKF have their working limits beyond which they will show consistency problems and have loss in accuracy [4].

## III. CONVERTED MEASUREMENT KALMAN FILTER

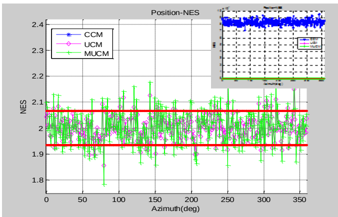
The polar to Cartesian conversion equations include a trigonometric function of a random variable. Though there are various issues with this type of conversion, two major issues to be considered are conversion and estimation bias. First the conversion introduces the bias in the mean of the converted random variable while using conventional conversion (1). The second is that the calculation of the converted measurement error covariance which requires the targets true range and bearing, unavailable in practice, so we have to evaluate the covariance using the measured position, this will introduce the correlation between measurement covariance estimate and the measurement error leading to an estimation bias when the converted measurements are used in tracking [8], [4], [2].

Consistency, conversion and estimation biases are evaluated for the following four conversion processes [4], [5], [6], and [7] in various ranges as specified in the simulation scenarios described in [11].

- Conventional Measurement Conversion (CCM)
- Unbiased Converted Measurement (UCM)
- Modified Unbiased Converted Measurement (MUCM)
- Decorrelated Unbiased Converted Measurement (DUCM)




a) Position Error (Cartesian) (b) Position Error(Polar)




(c) Normalized Error Square (NES) Analysis

Fig6. Evaluation of conversion bias and consistency for the target at Rang = 250 km, Azimuth =45 deg, $\sigma_r$ = 50 m and $\sigma_a$ = 15 deg.

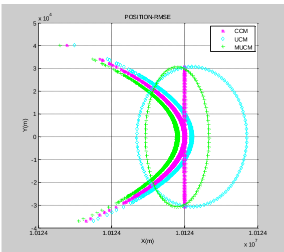
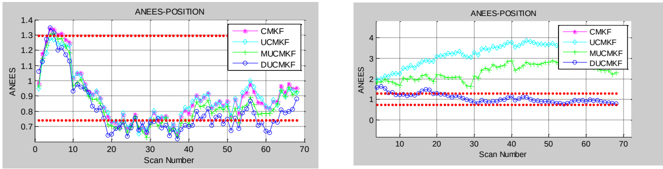



Fig7. Measurement uncertainty in Cartesian coordinate and Gaussian approximation by conversion methods for the target at Rang = 10124 km, Azimuth = 0 deg, $\sigma_r$ = 0.2 m and $\sigma_a$ = 2 mrad

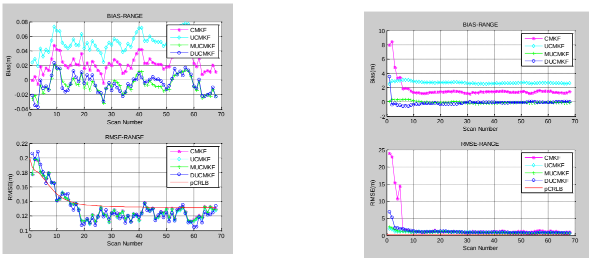
From the Fig.6 (a) and Fig. 6(b) CCM and MUCM introduce bias in the mean of the converted measurement while UCM is the only method produces the unbiased conversion. Fig6 (c) shows except CCM, other two methods are consistent and the reason for the inconsistency in CCM is explained in Fig7, i.e. poorly approximated measurement covariance in Cartesian coordinate. DUCM needed predicted position for the covariance calculation so its conversion bias was not evaluated.

Since it is a modified version of UCM, DUCM is also an unbiased and consistent conversion method [2].




(a) Short Range (50 km) (b) Long Range (2711.5 km)

Fig.8 Consistency evaluation of Kalman filter which uses the different measurement conversion methods for the target at short and long ranges, Azimuth of 67.218 deg , $\sigma_r$ = 0.2 m ,$\sigma_a$ = 2 mrad and number of Monte Carlo runs = 100.




(a) Short Range (b) Long Range

Fig.9 Evaluation of Estimation bias for that target at short and long ranges, Azimuth of 67.218 deg , $\sigma_r$ = 0.2 m ,$\sigma_a$ = 2 mrad and Number of Monte Carlo runs = 100.

Fig.8 and Fig.9 shows that all four methods gives acceptable performance in short range but as the range increases bias and consistency problems are more visible.

TABLE-1 Conversion and Estimation Bias

| S. No | Algorithm | Conversion Bias | Estimation Bias | Filter Output |
|---|---|---|---|---|
| 1 | CCMKF | Biased | Biased | Biased |
| 2 | UCMKF | Unbiased | Biased | Biased |
| 3 | MUCMKF | Biased | Biased | Unbiased |
| 4 | DUCMKF | Unbiased | Unbiased | Unbiased |

Results are tabulated in Table-1, since both conversion and estimated biases are opposite in nature for MUCMKF, the final output will be unbiased. DUCMKF is the only filter which is consistent, unbiased and gives better RMSE performance among four methods.

## IV. MIXED COORDINATE FILTER

In the "mixed coordinate" EKF the state is maintained in Cartesian coordinates and the measurements are utilized in their polar form. There is a nonlinear measurement prediction equation and linearization of the measurement equation is required for the state and covariance update [4]. From section II it was concluded that EKF becomes inconsistent in long ranges due to severe non linearity introduced in the measurement equation. Filter divergence in many nonlinear filtering problems occurs only when the track accuracy is low. If the track is accurate enough, local linearization can be effectively used, and the EKF will yield consistent and near-optimal tracking performance. MCAEKF guarantees the overall consistency of EKF by adaptively changing the measurement covariance matrix in the early stage of filtering. The only drawback of the MCA approach is that it has range accuracy loss in the early stages of the filtering due to the intentionally enlarged measurement noise covariance.

Key for the MCAEKF is to characterize and quantify the curvature of the posterior uncertainty region. Fig.10 shows a converted measurement uncertainty region and approximated the Gaussian uncertainty with the same center and thickness. The "distance" *DC* characterize the impact of the curvature at a point in the curved uncertainty region to the corresponding Gaussian uncertainty region.

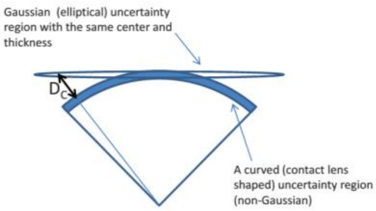



Fig 10. The quantification of the curvature of a curved uncertainty region

For a point $X = [\,x \quad \dot{x} \quad y \quad \dot{y}\,]'$ in the curved uncertainty region, from simple geometry one has

$$r^e = \sqrt{\hat{x}^2 + \hat{y}^2} \tag{9}$$

$$r^p = \frac{(x\hat{x}+y\hat{y})}{\sqrt{(x^2+y^2)}} \tag{10}$$

where $r^e$ is the range at $\hat{x}$ , $r^p$ is the range $r^e$ projected on $x$. From simple geometry one has

$$D_C^r(X) = \frac{(r^e)^2}{r^p} - r^e \tag{11}$$

The distance $D_C^r(X)$ is interpreted as the error introduced by the corresponding measurement nonlinearity. Find the minimum required measurement covariance to ensure consistency by providing sufficient intersection between predicated and measurement uncertainties as per steps in [9].

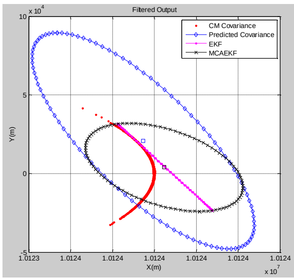
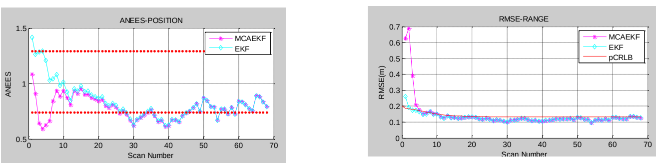
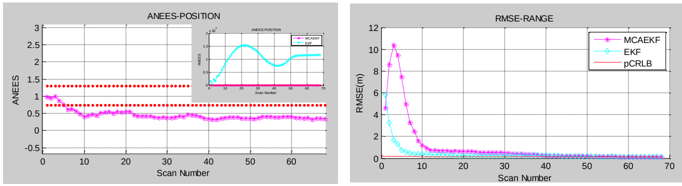



Fig.11 Filtered Output in the 3rd scan for the EKF and MCAEKF filter, target at long range, azimuth of 0 deg , $\sigma_r$ = 0.2 m ,$\sigma_a$ = 2 mrad

Filter divergence in EKF is explained in Fig.11, where intersection of measured and predicted measurement (Significant Region (SR)) [9] is not covered by the EKF's filtered output, leads to inconsistency. But MCAEKF's filtered output covers entire SR due to inflated measurement covariance, this in turn ensures the consistency.




(a) Short Range




(b) Long Range

Fig.12, Evaluation of consistency and RMSE in range for that target at short, long ranges, Azimuth of 67.218 deg , $\sigma_r$ = 0.2 m ,$\sigma_a$ = 2 mrad and Number of Monte Carlo runs = 100.

From the Fig.12, MCAEKF overcomes the consistency problem in EKF for long range targets by sacrificing range accuracy in the early stages of filtering.

## V. REGULARIZED PARTICLE FILTER(RPF)

The key idea of the particle filter is to represent the Bayesian filter's posterior density by the random set of weighted samples (point masses). As the number of samples becomes very large they effectively provide an exact equivalent representation to the usual functional description of the posterior pdf. Estimate of the moments such as mean and covariance can be obtained directly from the samples. The basic particle filter encounters two significant problems namely particle degeneracy and sample impoverishment [13]. Many particle filter versions exist that attempt to alleviate these problems by choosing proper importance density and resampling. A recent study shows that for the banana problem, version of the particle filter called Regularized Particle Filter [11] gives the optimal performance and it is evaluated in this section.

The regularized particle filter attempts to avoid the problem of sample impoverishment by changing how the resampling step is done in the particle filter. The resampling step samples particles from a discrete distribution which creates exact duplicate particles, leading to the impoverishment problem in the standard method. If samples are instead taken from a continuous approximation of the posterior density, no such duplication of particles will occur and this problem should be prevented. After initializing a set of particles, through the use of two-point differencing, the particle filter algorithm would then proceed as in [11] during each iteration (prior density is assumed as a proposal density).

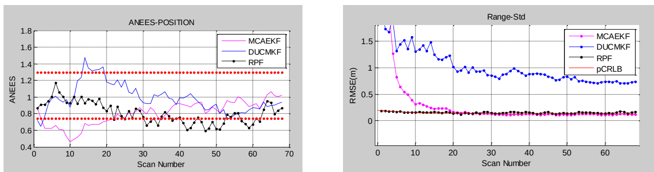



Fig.13 Consistency and RMSE Test for RPF in Long Range target scenarios

From the Fig.13, RPF ensures consistency and achieves better RMSE in long range scenarios including early state performance at the expense of computational power.

## VI. MARGINALIZED PARTICLE FILTER(MPF)

Particle filters are the general solution to nonlinear and nonGaussian estimation problems and in general it requires a heavy computational power. If there is a linear sub-structure in the state-space model, this can be utilized in order to obtain better estimates and possibly reduce the computational demands [14], [15]. The idea is to partition the state vector according to

$$x_t = \begin{bmatrix} x_t^l \\ x_t^n \end{bmatrix} \tag{12}$$

Where $x_t^l$ denotes the state variable with conditional linear dynamics and $x_t^n$ denotes the nonlinear state variable. Using Bayes' theorem linear state variable can be marginalized out and estimated using a finite-dimensional optimal filter. The remaining nonlinear state variables are then estimated using the particle filter. This is sometimes referred to as Rao-Blackwellization [14].

The long range scenario we consider in this work has linear state equation and nonlinear measurement equation with Gaussian process and measurement noise. Since the position in the state vector is nonlinearly related the measurement, it is treated as a nonlinear state variable and velocities are treated as linear state variables. Linear and nonlinear state variables are defined as

$$x_t = \begin{bmatrix} x_t^l \\ x_t^n \end{bmatrix} \tag{13}$$

$$x_t^l = [\, x, y]' \tag{14}$$

$$x_t^n = [\, v_x, v_y]' \tag{15}$$

Where $x_t = [\, x, v_x, y, v_y]'$ is a state vector. The generalized model described in [14] can be reduced as follows

$$x_{t+1}^n = A_n^n x_t^n + A_l^n x_t^l + w_t^n \tag{16}$$

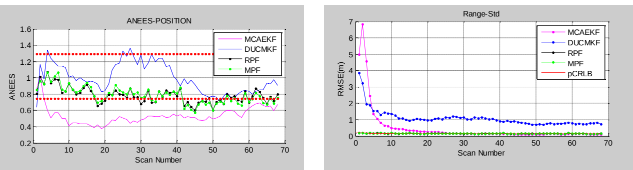
$$x_{t+1}^l = \quad A_l^l x_t^l + w_t^l \tag{17}$$

$$y_t = h_t(x_t^n) \; + e_t \tag{18}$$

Since $A_n^n, A_l^n, A_l^l, G^n$ and $G^l$ are independent of $x_t^n$ and $G^n = G^l = I$ .

$$P_{t/t}^{(i)} = P_{t/t} \quad \text{for} \quad i = 1,2,3 \ldots \ldots N \tag{19}$$

Where $N$ is the total number of particle and $P_{t/t}^{(i)}$ is the Kalman filter covariance associated with each the particle $i$ .According to (19) only one instead of $N$ Riccati recursions is needed, which leads to a substantial reduction in computational complexity [15]. This is, of course, very important in real-time implementations. Since the measurement equation (18) does not contain any information about the linear state variables $x_t^l$ , actual measurements can't be used to update the linear state variables. Instead, all information from the measurements enters the Kalman filter implicitly via the second measurement update. Flow chart in the Fig.15 explains the process in MPF for banana problem.




(a) ANEES in Position (b) Position Error

Fig.14 Consistency and RMSE Test for MPF with Resampling and Regularization in Long Range Target Scenario Defined in Section 2.3.

From the fig 14, it is observed that, with the same number of particles (as particle filter) MPF achieves better performance in less time compared to RPF.

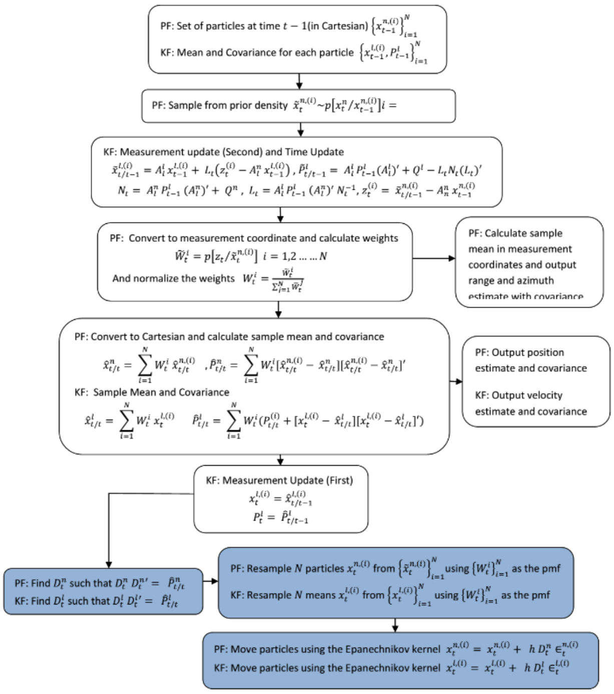



Fig.15 MPF Flow Chart with Regularization

## VII. Simulation Results

Monte Carlo simulations are carried for long range target scenario defined in [11] to analyze the performance benefits of the MPF compared to RPF.

TABLE-2 Constant Time Simulation

| Parameter | RPF | MPF |
|---|---|---|
| No of Particles | 10000 | 11000 |
| RMSE Position(m) | 906 | 848 |
| RMSE Velocity(m/s) | 119.51 | 115.45 |
| RMSE Range (m) | 0.1582 | 0.1581 |
| RMSE Azimuth(deg) | 0.0191 | 0.0178 |
| Time (s) | 0.8711 | 0.8803 |
| No of Monte Carlo Runs | 1000 | |

TABLE-3 Constant Velocity RMSE Simulation

| Parameter | RPF | MPF |
|---|---|---|
| No of Particles | 10000 | 8000 |
| RMSE Position(m) | 938 | 880 |
| RMSE Velocity(m/s) | 121.37 | 122.05 |
| RMSE Range (m) | 0.1585 | 0.1588 |
| RMSE Azimuth(deg) | 0.0197 | 0.0185 |
| Time (s) | 0.8790 | 0.6402 |
| No of Monte Carlo Runs | 1000 | |

From table 2, it is observed that for a given computational cost (constant execution time) MPF performs better than RPF. MPF can accommodate more number of particles in the given execution time compared to RPF, which makes MPFs performance superior compared to RPF. From table 3 for a given velocity RMSE (constant velocity RMSE), MPF achieves the target with less number of the particle than RPF. Particles in MPF occupies the two-dimensional space, instead, in RPF it occupies four-dimensional space, so less number of particles are sufficient to achieve the given target in MPF compared to RPF.

## VI. CONCLUSION

In the present work, use of the marginalization has been explored for the banana problem present in 2D long range tracking Radar to reduce the computational complexity of the existing particle filter solution. MPF, which is a powerful combination of PF and KF uses the linear substructure with Gaussian process noise present in the target model to reduce the computational complexity of the particle filter. Existing solutions based on the CMKF, MCF and RPF was evaluated, from the results RPF outperforms the two methods by sacrificing computational cost.

Proposed MPF solution for the banana problem has been thoroughly analyzed in a long range scenario and it was observed that for a given computational cost, MPF performance is better than the RPF and for the given accuracy requirement, MPF achieves with less number of particles compared to RPF in the long range tracking scenario for the banana problem.

As the range increases the amount of nonGaussianity present in the uncertainty region of the converted measurement increases which require more number of particles to achieve optimal performance, so a general solution which works for all ranges like DUCMKF may be attempted in future in the particle filter framework.

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