Target Tracking using MCMC and KLD Particle Filters

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***Abstract*—As the target performs random movements, the state variables are restricted to nonlinear model. In general, we observe non-Gaussian noise in target tracking application. So we can apply particle filtering algorithm to this system, however it has many drawbacks. In order to overcome these negative aspects, advanced techniques are implemented. Different algorithms like *Markov Chain Monte Carlo* particle filter *(MCMC PF)*, *Kullback-Lerbler Distance* Sampling particle filter *(KLD PF)* are used in radar target tracking for analyzing in terms of signal to noise (SNR) ratio, Mean square error (MSE) and the standard error of mean (SEM). The simulation results are represented for MCMC particle filter and KLD Sampling. Therefore, we represent KLD Sampling particle filter is more optimized technique to the target tracking.**

Keyword- KLD-Sampling, MCMC Particle Filter, MSE, SNR, Standard Estimation, SEM.

I. INTRODUCTION

In engineering, nonlinearity is a frequent problem in the application of filters [1][2][3]. The dynamic stochastic process is estimated using noisy observations. In this paper, these problems are overcome in the application of radar tracking where the parameters of the target are to be determined. The problems are described in Dynamic State Space model (DSS) of an unobserved state variable which provides time varying dynamics X_k. The probability distribution is $p(X_k,X_{k-1})$ where k is any physical quantity (time). The observations Y_k in the application are combined version of noise and X_k. The distribution $p(Y_k / X_k)$ represents the conditional probability of observation equation on the unknown state variable X_k. The model is represented as:

$X_k = f(X_{k-1})+U_k$ (State equation) 1.1

$Y_k = h(X_k)+V_k$ (Measurement equation) 1.2

Where U_k, V_k are state and measurement noise. State estimation problems are resolved using particle filters in various applications of navigation and fault detection [5]. Particle filters can represent random probability densities which make them possible to overcome the problems of nonlinear and non-Gaussian estimation [4]. Even though particle filters are better for implementation, there are some limitations as it provides less diversity and computational complexity for more number of samples resulting in the divergence of particle filter [2].

In present scenario a new algorithm has been introduced to overcome the less diversity and computational complexity problems. The less diversity is overcome by MCMC sampling process whereas computational complexity is increased [11]. In the statistical approach with the modification in size of sample sets the efficiency gradually increased for particle filters. An adaptive approach like Kullback-Lerbler distance (KLD) sampling is proposed which provides significant improvement in the computational complexity [13]. The principle of KLD Sampling method is used to reduce the approximation error due to sample based representation. The total number of samples chosen is determined by the uncertainty in this approach.

II. KLD ALGORITHM

This approach limits the selection of Samples that are estimated from the particle filter providing error. The discrete constant distribution form is used in assumed as true posterior. Here the samples distance between maximum likelihood estimate (MLE) and true posterior [13] is determined.

Let us consider *n* samples from a discrete distribution having *k* distinct bins.

Let **S** represents the samples taken from each set. $\boldsymbol{S}=(S_1, S_2 \ldots S_k)$.

Let **S** is distributed as **S**=~Multinomial (n, **p**). Where the probability of each set is $\mathbf{p}=p_1, p_2 \ldots p_k$. The MLE (maximum likelihood estimate) of this probability is specified as $\hat{\boldsymbol{p}}=n^{-1}\mathbf{S}$. The likelihood statistic ratio λ_n for testing the probability is

$$\log \lambda_n=\sum_{j=1}^{k} \log\left(\frac{\hat{p}_j}{p_j}\right) = n\sum_{j=1}^{k} \hat{p}_j * \log\left(\frac{\hat{p}_j}{p_j}\right) \qquad .2.1$$

This gives the minimum distance, referred as *K-L distance*, between the MLE and the true distribution.

P (K≤ϵ) = P (2nK≤2nϵ) = P (χ^2_{k-1}≤2nϵ) 2.2

This expression is valid when **p,** the true distribution, is the likelihood ratio come together to a chi-square distribution. Combining this with the quantities of Chi-square distribution,

P (K≤ϵ) =1-δ 2.5

By choosing the samples appropriate, as

$$n = \frac{1}{2\epsilon} x^2_{k-1,1-\delta} \quad .2.6$$

With a probability of 1-δ, the KL distance between MLE and true distribution is obtained less than ϵ. A better selection of *n* can be done by Wilson-Hilferty transformation as

$$n_x = \frac{s-1}{2\epsilon}\left\{1 - \frac{2}{9(s-1)} + \sqrt{\frac{2}{9(s-1)}} z_{1-\delta}\right\}^3 \quad 2.7$$

Hence the resulting approach is KLD-sampling algorithm since it is related to Kullback-Lerbler distance.

1. The Probability Mass Function of the preliminary state $p(x_0)$ is known.
2. Generate ***N i***nitial particles ($x_{0,i}^{+)}$ on the basis of the pdf $p(x_{0)}$. (i=0,1,….N)
3. For k=1,2,… do
4. Do time propagation step to get prior particles ($x_{k,i}$).
   $x_{k,i}^- = f(x_{k-1,i}^+)+u_k$ (i=1 ,2,…N)
5. Compute the weights (w_i) of each particle ($x_{k,i}^-$).
6. Normalize the weights as
   $w_i = w_i$ /sum (w_j) (j=1,2….N)
   //KLD sampling algorithm\\
7. Initialization : s=0, i=0, N=1, all bins are zero resampled
8. While(i≤N and i≤N_{max}) do
   Using multinomial resampling we will select one particle as per the weights from particle set: i=i+1.
9. If ($x_k^{(n)}$ falls into an zero resampled bin b) then
10. s=s+1;
11. b=non-zero resampled;
12. if (n≥n_{xmin}) then
13. $n_x = \frac{s-1}{2\epsilon}\left\{1 - \frac{2}{9(s-1)} + \sqrt{\frac{2}{9(s-1)}} z_{1-\delta}\right\}^3$
14. n=n+1
15. Return x_k

III. MCMC ALGORITHM

Particle filters are popular in solving nonlinear and non-Gaussian state estimation problems. There is a drawback in particle filter which provide less diversity which overcome using MCMC PF [11]. Here MCMC particle filtering is used to swap the standard sampling to increase the diversity and allows to handle better dimensional state spaces, which standard PF cannot provide.

The steps for MCMC algorithm are as follows:

1. The Probability Mass Function of the preliminary state $p(x_0)$ is known.
2. Generate ***N*** initial particles ($x_{0,i}^+$) on the basis of the pdf $p(x_0)$. (i=0,1,….N)
3. For k=1,2,… do
4. Do time propagation step to get prior particles ($x_{k,i}$).
   $x_{k,i}^- = f(x_{k-1,i}^+)+u_k$ (i=1,2,…N)
5. Compute the weights (w_i) of each particle ($x_{k,i}^-$).
6. Normalize the weights as
   $w_i = w_i$ /sum (w_j) (j=1,2….N)
   //MCMC sampling algorithm\\
7. Sample u~U [0, 1].
8. Get the new particles $x_{k,i}^*$ from $p(x_k/ x_{k-1,i})$.
9. If u < min{1, $p(y_k/ x_{k,i}^*)$ / $p(y_k/ x_{k,i}^-)$}
   $x_{k,i} = x_{k,i}^*$
   else $x_{k,i} = x_{k,i}^-$
10. Return x_k

IV. SIMULATION RESULTS

The simulation code in Matlab was used for analysis of the performance of two algorithms, in Pentium pro with 2.0GHz and 2GB RAM. For the comparison of the performance of the two methods in target tracking as discussed above, the system was simulated using dynamic state space model. Thereafter, the simulation of the Monte Carlo Markov chain PF, the KLD sampling particle filter has been done. The analytical comparison was performed for the simulation results obtained.

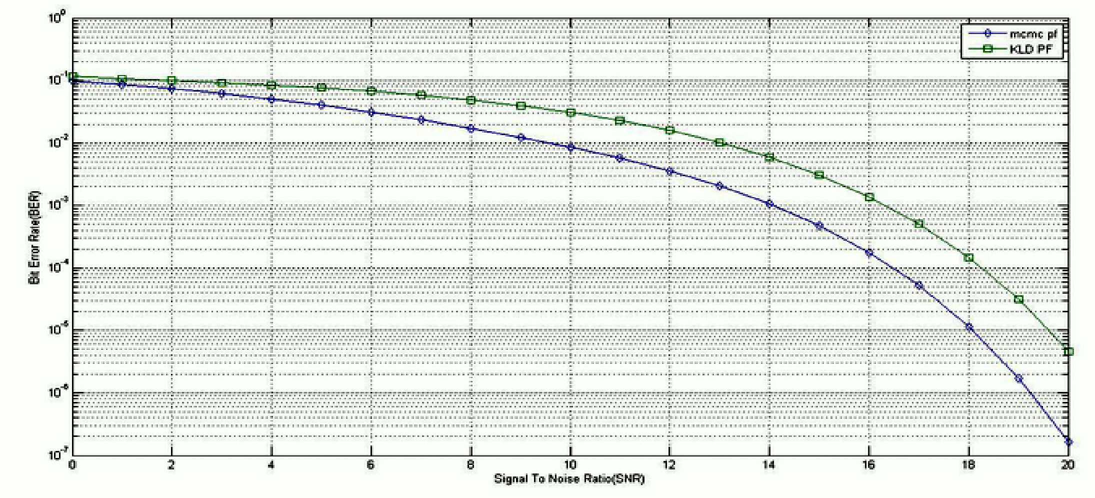

Fig 1: SNR vs BER for radar tracking

Figure 1 shows the SNR to BER relation for the two algorithms considering N = 300. From the figure, it is clearly observed that each algorithm has better tracking performance but MCMC particle filter outperforms KLD particle filter.

Figure 2 provides the comparison between the mean square error for the KLD and MCMC particle filter. From the graph, it is observed that the value of MSE for KLD and MCMC are very low and almost same**.** Thus we can say that these algorithms can provide better Convergence consistency and uniform MSE distribution resulting in good estimation for nonlinear and non-Gaussian state estimation problem.

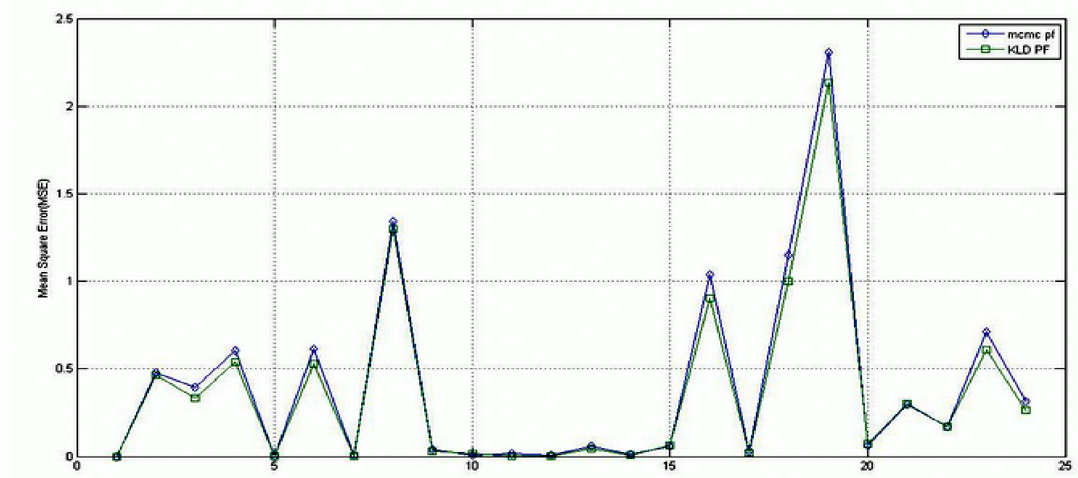

Fig 2: MSE Curve for radar Tracking

Table 1: MSE for MCMC PF, KLD PF

	MSE				Run time (s)
	Mean	**Variance**	**Standard deviation**	**SEM**	
MCMC PF	0.3984	0.2929	0.5412	0.1105	1.931 s
KLD sampling PF	0.3657	0.2722	0.5217	0.1065	0.849 s

From table 1 and figure 2, constructing density function and optimizing the proposed distribution for gradual increase in diversity of particles through MCMC algorithm which takes the state estimates as a reference of updated measurement which represents state estimation more precise and efficient. As we can see standard error of mean (SEM) is low for KLD particle filter than MCMC particle filter. It makes the state estimation more accurate and effective. The more effective samples, the higher will be the estimation accuracy.

The execution time performance of the MCMC algorithm is obtained to be 1.9s where as for the KLD algorithm is 0.84s. Hence the computational complexity is reduced using the KLD algorithm. It means the estimation accuracy is obtained with only 50% of the computational time of MCMC PF. In contrast MCMC algorithm is better in diversity problem but KLD PF is competitor with MCMC PF. In computational complexity KLD algorithm dominates MCMC PF. So, finally tracking accuracy is improved by KLD PF.

V. CONCLUSION

The proposed work in this manuscript is having a lot of potential for future scope in the area of radar target tracking system ensuring that the work is versatile and flexible. The research of tracking can be extended using different new techniques in the analysis of mean square error (MSE). Adaptive algorithms are suited for target tracking in estimation for nonlinear states. Finally we conclude that KLD sampling particle filter provides better performance in target tracking even it has less diversity than MCMC particle filter.

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