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Article

A Novel Approach to Overcome Sample Impoverishment Problem of Particle Filter using Chaotic Crow Search Algorithm

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A B S T R A C T

Generic Particle Filter is extensively used in the area of computer vision for non-Linear and non-Gaussian state estimation. However, Generic Particle Filter suffers from the problem of sample impoverishment and particle degeneracy. Aim of the research paper is to propose a method, using Chaotic Crow Search Algorithm as resampling method to overcome these problems of generic particle filter. The proposed method has been simulated on benchmark 1-D and 2-D state estimation problems. Simulation results of the proposed method are compared with Generic Particle Filter, Particle Filter- Particle Swarm Optimization and Particle Filter-Backtracking Search Optimization. On average of the outcome, we have achieved RMSE value of 2.0214 for 1-D problem and value of 0.0281 for 2-D problem for the proposed method. Results demonstrate that our method not only outperforms other methods but also achieve high accuracy with minimum computational requirement.

Keywords: Particle Filter, CCSA, Sample Impoverishment, Particle Degeneracy

Introduction

Generic Particle Filter (GPF) is based on Sequential Monte-Carlo framework. GPF has been widely explored in the fields of science, artificial intelligence, Robot intelligence, military, target detection etc. However, GPF is suffered from two fundamental problems of particle degeneracy and sample impoverishment.[1] Resampling techniques like Sequential resampling, Partial resampling were explored with GPF to address these problems but there is still scope of improvement.

Now a day, meta heuristics optimization techniques are very popular to improve the performance of GPF by catering its problems. These techniques have a fast convergence rate and reach to optimal solution with less computational effort. There are many swarms and evolutionary optimization techniques like PSO (Particle Swarm Optimization)[3], GSA (Gravitational Search Algorithm)[4], BA (Bat Algorithm)[5], FA (Firefly Algorithm)[6], Modified Genetic Algorithm (MGA), Backtracking Search Optimization (BSA) etc. were used with GPF to address its problems.

In[8] PSO was used with GPF to identify the likelihood sample area. Particles were then distributed based on the base points to improve their contribution for state estimation. In[9] FA was used as resampling technique. FA reduced the search area for better estimation by changing the location of the particles. But FA was not able to recover from local minima and hence, lost the target. In[10] Spider Monkey Optimization was proposed also in GPF framework to address its problems. This method updated the particles position based on local and global leader phase for better state estimation. However, in[11] optimization was applied with particle filter to categorise the particles as male and female to ensure diversity in search space in order to address sample degeneracy. In addition,[12] addressed GPF problems using BA. This technique accumulated the particles in high likelihood region for better state estimation. In[13] MGA was exploited in GPF framework. Crossover and mutation probabilities were calculated based on the degree of particle degeneracy to ensure diversity in the search space. However, such calculations slow the state estimation. In[17], author proposed BSA as optimization in PF framework for state estimation. It had used memory for prediction of next state in the estimation problem. Few literatures are tabulated in Table 1 for better understanding of the topic.

In our work, we have used Chaotic Crow Search Optimization (CCSA) as resampling technique under GPF framework for state estimation in benchmark 1-D and 2-D bearing only problems. CSA is a nature inspired meta-heuristic approach proposed in.[7] CCSA when used as resampling technique in GPF ensures better state estimation by catering its fundamental problems. The rest of the paper is organised as follows:

Section 2 discusses theory and methodology of the proposed method. PF-CCSA is presented in section.

Approach has been represented diagrammatically. The experimental validation of the proposed work is discussed in Section 4. Results are compared with other state-of-the-art and are tabulated for both 1-D and 2-D benchmark problems. Section 5 concludes the work and sketched the future direction of the work.

Table 1.State-of-the-art work with GPF

Technique	Summary
Particle Filter based on PSO	Likelihood sample area was identified by PSO for efficient results
Particle Filter based on FA	Optimize particle number to handle the sample impoverishment
Particle Filter based on Spider monkey	Quality of particles was improved by updating them locally and globally in search space.
Particle Filter based on Social spider	Particles were partitioned into groups of male and female for better state estimation.
Particle Filter based on BA	Particles were moved to high likelihood area by Bat algorithm.
Particle Filter Based on Improved Genetic Algorithm Resampling	Simple resampling and elitist selection were utilized for weight selection of particles.
Particle Filter based on Back Tracking Search Optimization	Memory to store prior generations for better target's state estimation.

The next section will cover the details about the GPF and the proposed resampling technique. The methodology of the proposed method is also discussed.

Theory and Methodology

In this section, we discuss about the required theory behind the particle filter and the proposed resampling technique CCSA.

GPF are based on Monte Carlo simulation and modified Baye's algorithms. The posterior distribution $p(X_{1...t}|Z_{1...t})$ and observation distribution $p(Z_{1...t})$[14] of the particles is considered to provide solution for estimation problems. State vector of the target denoted by $X_t \in R^d$ with $X_{1...t} = \{X_{1,} \dots X_t\}$ to estimate the posterior distribution and observation vector $Z_t \in R^d$ with $Z_{1...t} = \{Z_1, \dots Z_t\}$ are represented as:

$$X_t = f_t(X_{t-1}) + M_t \quad (1)$$

$$Z_t = h_t(X_t) + N_t \quad (2)$$

Where, $f_t, h_t : R^d \, X \, R^d \rightarrow R^d$ are system observation functions. M_t and N_t are noise sequences. The state positions X_t of all samples at each time t based on previous observations $p(Z_{1...t})$ is used for constructing the PDF for the stages: prediction stage and update stage.[15] The PDF of the state at time t considering all the previous observations at this point is given by the equation:

$$p(X_{1...t}|Z_{1...t}) = \int p(X_t|X_{t-1})\, p(X_{t-1}|Z_{1:t-1})\, \mathrm{dX}_{t-1} \quad (3)$$

Where, $p(X_t|X_{t-1})$ is the Markov model determined by Eq. (1). This is the prediction state of GPF which is followed by update state. The observation Z_t at time *t* is represented by Baye's posterior density and is given by the following Eq. (4).

$$p(X_{1...t}|Z_{1...t}) = \frac{p(X_t|Z_t)\, p(X_t|Z_{1:t-1})}{p(Z_t|Z_{1:t-1})} \quad (4)$$

Random weights are assigned to each particle for the estimation process. Particles are sampled according to their posterior probability During the estimation process, the particles are moving randomly in the search space. Particles which are far from the high likelihood region are having negligible weight. These particles do not contribute much for the state estimation process and need to be replaced by the particles with better weight to improve their contribution. Resampling technique is used in GPF framework to enhance particle distribution in the high likelihood area. The proposed resampling based on Chaotic Crow Search optimization to overcome GPF shortcomings.

CCSA is a population based Meta Heuristic Optimization technique.[7] It has two factors for ensuring diversity in search space a) Awareness probability b) Flight length. In CCSA based resampling, the particles are considered as crow population (N). $x_{k,t}$ represents the position of *k* crow at time *t* in the search space. Here, *k* = 1,2...*N* and = 1,2,...t_{max}. At time *t*, crow *j* wants to visit its hidden food store, $s_{j,t}$ and is followed by crow *k*. Then, the position of the crow in the search space is updated using the Eq. (5).

$$x_{k,t+1} = \begin{cases} x_{k,t} + r_k\, X\, fl_{k,t}^{chao} X\ (s_{j,t} - x_{k,t}) r_k \geq AP_{k,t} \\ a\ random\ position\ otherwise \end{cases} \quad (5)$$

Where, $fl_{k,t}^{chao}$ represents the flight length of crow *k* at time *t* which is evolved chaotically, $AP_{k,t}$ denotes the awareness probability of crow *k* at time *t* and $r_k \in [0,1]$. The next section will brief about our proposed solution to tackle sample impoverishment.

Proposed solution for Sample Impoverishment

CCSA is proposed as resampling technique to solve the GPF problems of particle impoverishment and particle degeneracy. CCSA controls the search space and improve position of the particles in the search space with two parameters: Awareness Probability (AP) and flight length (fl). AP adaptively decreases or increases to control diversification and intensification of the particles in the search space ensure faster convergence. Flight length is evolved chaotically. The approach is discussed below.

Particles are randomly initialized as crow population and helps in identifying the true states in the search space. Position and memory of crow is initialised randomly as particle weight in search space. New position of the crow is updated in the search space using Eq. (5). The feasibility of the new position of each crow is checked on the basis of AP. Depending on feasibility, either crow updates its position or remains in the current location. New weights are calculated for each crow whose position is updated. The position of the hidden food is updated by choosing certain crow randomly. The memory is updated chaotically using the Eq. (6).

$$m_{k,t+1} = \begin{cases} x_{k,t+1}\ w(x_{k,t+1})\ is\ better\ than\ w(m_{k,t}) \\ m_{k,t}\ \ otherwise \end{cases} \quad (6)$$

where w(.) denotes the value of weight for each crow. Crow updates their memory and final position based on the value of weights. These steps are repeated for each crow till the weights are not optimized. The proposed method is presented in Figure 1.

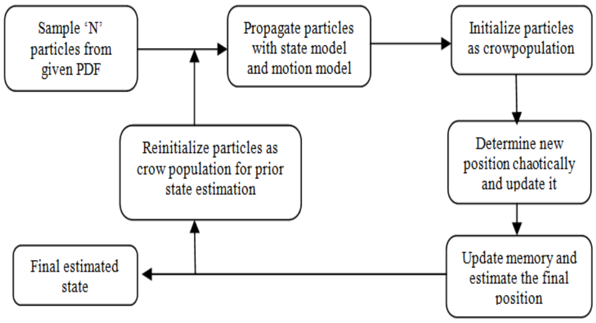


Figure 1.The Proposed Method (PF-CCSA)

For our proposed method we consider crow population size N to 500. Awareness probability varies from 0 to 1. 50 true states are considered for estimation. Hidden place and initial position of crow is considered same for first iteration as they have no experience. We applied our method for benchmark estimation problems of 1-D and 2-D bearing only tracking problem. The next section will present the simulation results.

Experimental Validation of Proposed Solution

Proposed solution has been simulated on Matlab 2015a on 2.53 GHz i5 processor. PF-CCSA is applied on two commonly used estimation problems a) 1-D non-linear problem b) Generic bearing only 2-D tracking problem. RMSE is used to for quantitative estimation of GPF, PF-PSO, PF-BSA and PF-CCSA and is calculated using Eq. (7).

$$RMSE_{Position} = \sqrt{\frac{\sum_{i=1}^{N}(X_{t.s.} - X_{e.s})^2}{N}} \quad (7)$$

where, *N* is the total number of different predictions, $X_{t.s.}$ denotes true state of the equation and $X_{e.s.}$ represents estimated state by the used method. These estimation problems are discussed below.

One Dimensional non-linear Problem

1-D uni-variant and non-linear problem was defined by.[15] Many authors had used this equation for state estimation.[8-12] One dimensional system target equation has been defined using Eq. (8).

$$X_t = \frac{X_{t-1}}{2} + 25\frac{X_{t-1}}{1+X_{t-1}^2} + 8\cos(1.2\,(t-1)) + w_t \quad (8)$$

The observation model equation is illustrated using Eq. (9).

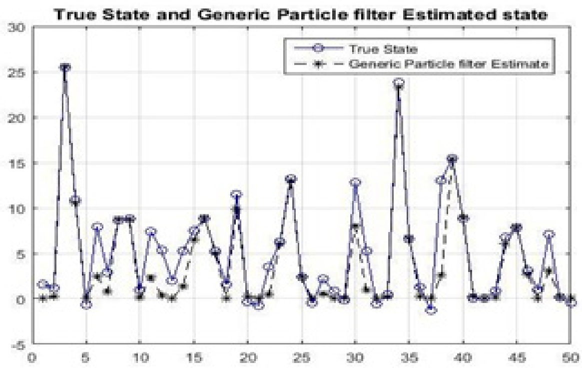
$$Z_t = \frac{X_t^2}{20} + v_t \quad (9)$$

where w_t and v_t are zero-mean Gaussian white noise with variances 10 and 1, respectively. The above equations are highly non-linear with the presence of cosine and square terms. Initialization parameters are taken as follows. Initial value of the system (X_t) is set to 0.1. 50 true states are considered for the estimation with population size of 500 crows.

Table 2, listed the RMSE and the running time of the considered methods. RMSE is calculated by taking mean of the error generated by iterating 10 times. Table's result inferred that our proposed method has lowest RMSE in comparison with other methods. GPF has the highest RMSE as there is no technique used to handle the sample impoverishment.

Table 2.Performance Comparison for 1-D non-linear Tracking Problem

Method	RMSE	Processing time
GPF [15]	5.5889	0.20 sec
PF-PSO [8]	3.7403	1.86 sec
PF-BSO [17]	2.2256	1.42 sec
PF-CCSA	2.0214	0.87 sec



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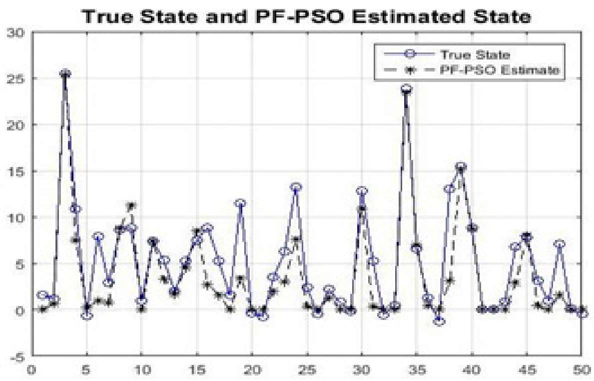

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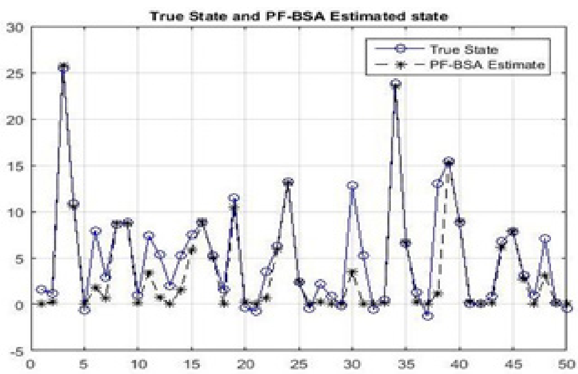

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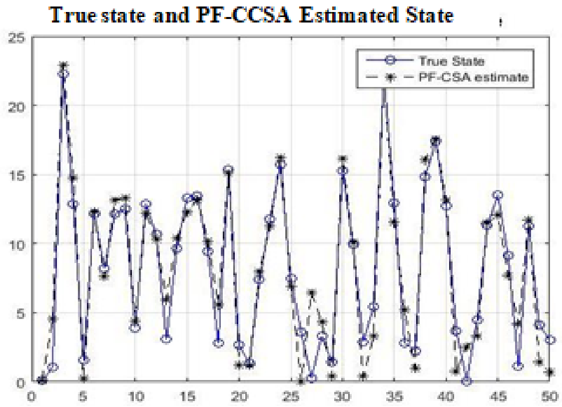
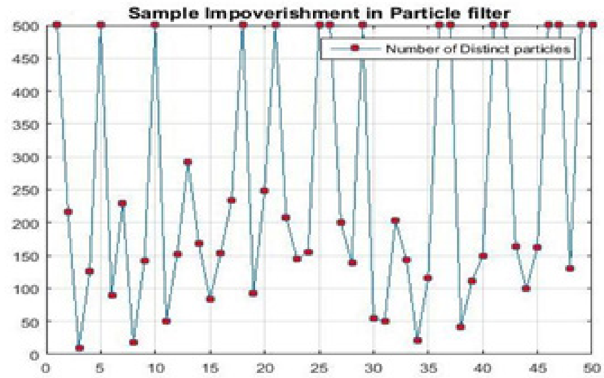


D

Figure 2.True state and Estimated state plot (a) GPF (b) PF-PSO (c) PF-BSA (d) PF-CCSA

Figure 2, shows plot of true state and estimated state for the considered methods for 1-D non-linear tracking problem. It has been illustrated from the plot that our method is able to show best and precise estimation of the states as compared to other methods.



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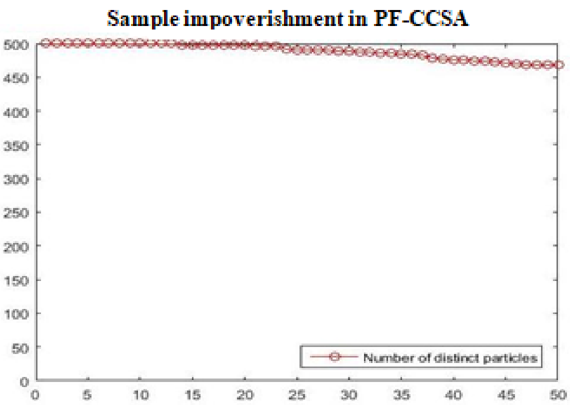

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Figure 3.Number of Distinct Particles for 1-D (a) GPF (b) PF-CCSA

The sample impoverishment is used as another performance metrics for comparison. For better state estimation, number of distinct particle at every state should be higher. Figure 3, shows the number of distinct number at every state for GPF and proposed method PF-CCSA. There are very few states for which all particles are distinct for GPF. However, our method has almost all distinct particles at each state. The bearing only 2-D tracking problem is discussed below.

Bearing only-2D Tracking Problem

In[15], target motion of system model is represented by the Eq. (10).

$$x_k = \emptyset\, x_{k-1} + w_k \qquad (10)$$

Where, at time k state is $x_k = (x, v_x, y, v_y)^t_k$ and zero mean system noise is $w_k = (w_x, w_y)^t_k$. v_x and v_y represent velocity in x and y direction respectively $\emptyset$ and is a 4 x 4 matrix.

Online measurement (Z_k) by the fixed observer at origin is determined using Eq. (11).[15]

$$Z_k = \tan^{-1}\frac{y_k}{x_k} + v_k \qquad (11)$$

Using the above Eqs. (10) and (11), the target movement in 2-dimentional is represented in the Figure 4.

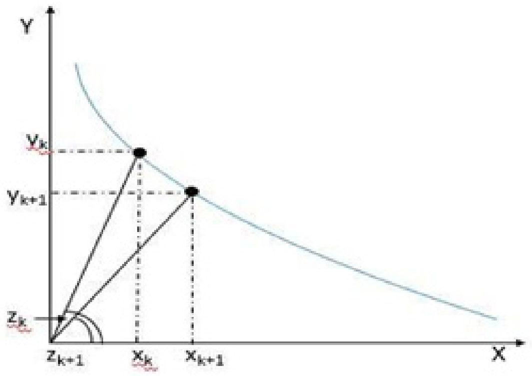


Figure 4.2-Dbearingonlytrackingproblem[15]

Table 3, Tabulated the performance for 2-D bearing only tracking problem for state-of-the-art. Results are obtained by iterating the code 10 times and taking their mean value. Simulation results inferred that our proposed method has the lowest error in comparison with others.

Table 3.Performance comparison for 2-D bearing only tracking problem

Method	RMSE 2-D	Processing time (sec)
GPF [15]	0.0744	2.47
PF-PSO [8]	0.0587	3.52
PF-BSA [17]	0.0378	2.98
PF-CCSA	0.0281	1.89

Performance for 2-D bearing only problem has been represented in the Figure 5. RMSE has been plotted for GPF, PF-PSO, PF-BSA and the proposed method. Results infer that the proposed method PF-CSA has estimated the target trajectory better as compared to other methods.

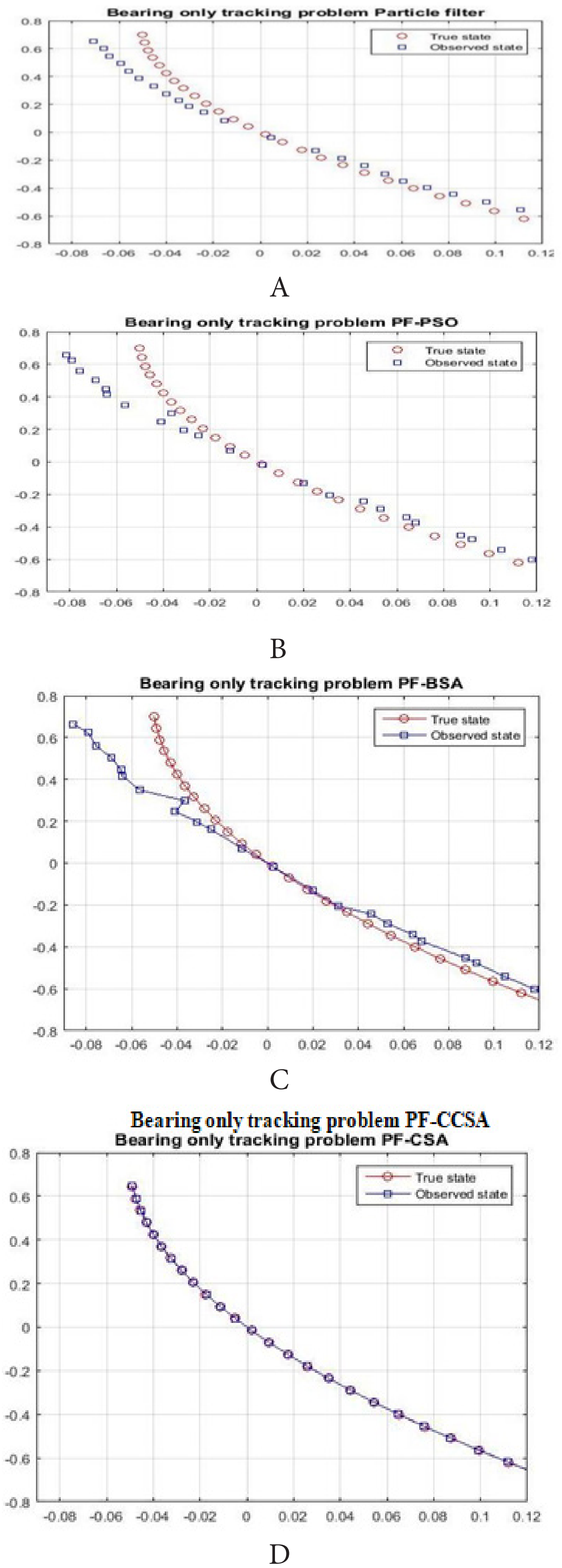
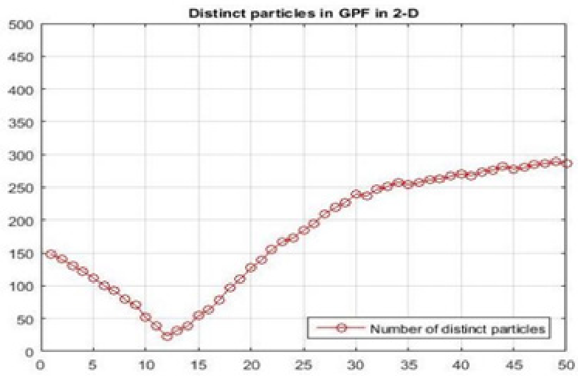


Figure 5.True state and Target trajectory estimation in 2-D (a) GPF (b) PF-PSO (c) PF-BSA (d) PF-CCSA



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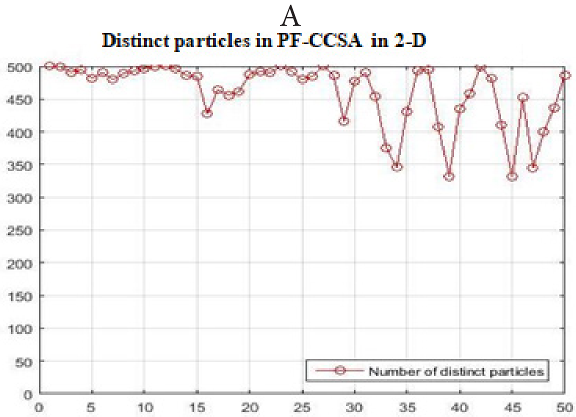

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Figure 6.Number of distinct particles for 2-D (a) GPF (b) PF-CCSA

Figure 6, Represents the sample impoverishment for GPF and our proposed method in 2-D bearing only tracking problem. Plot shows that PF-CSA has maximum numbers of stages with almost all the distinct particles. Sample impoverishment problem is tackled in a very graceful manner by the proposed method. The next section will conclude the work and also, discuss the future scope of our work.

Conclusion and Future Direction

In this work, Chaotic Crow search algorithm has been proposed as resampling technique in particle filter framework. Fundamental problems particle degeneracy and sample impoverishment of particle filter has been catered to a great extent. The proposed method converges to optimal solution very fast and memory of the optimization algorithm generates better estimation. From the simulation results, it is evident that the proposed method has least RMSE in comparison to other state-of-the-art. Results of benchmark problems of 1-D and 2-D revealed that our proposed approach is suitable for real time tracking and can achieve high accuracy with less computational efforts. In future, the proposed approach can be used for tracking object trajectory in video sequences.

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