Four Different Methods to Hybrid Simulated Kalman Filter (SKF) with Particle Swarm Optimization (PSO)

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Abstract—This paper presents a performance evaluation of a new hybrid Simulated Kalman Filter and Particle Swarm Optimization (SKF-PSO), for continuous numerical optimization problems. Simulated Kalman filter (SKF) was inspired by the estimation capability of Kalman filter. Every agent in SKF is regarded as a Kalman filter. Inspired by the bird flocking, Particle Swarm Optimization (PSO), has been introduced in 1994. Four methods (models) to hybridize SKF and PSO are proposed in this paper. The performance of the hybrid SKF-PSO algorithms is compared against the original SKF using CEC2014 benchmark dataset for continuous numerical optimization problems. Based on the analysis of experimental results, we found that model 3 and model 4 are performed better than the original SKF.

Keywords— Simulated Kalman Filter, Hybrid Simulated Kalman Filter, Continuous Numerical Optimization Problems

1. INTRODUCTION

The main objective of an optimization problem is to find the best combination of real-valued variables of a fitness function such that the value of the fitness is maximum or minimum. This can be achieved efficiently by employing a population-based optimization algorithm. The simulated Kalman filter (SKF) [1] and Particle Swarm Optimization (PSO) [2] are examples of population-based optimization algorithms. SKF has been applied to solve various optimization problems [3]–[8]. In this study, hybridization between SKF with PSO is presented. Specifically, 4 different methods to hybrid SKF with PSO are presented in this paper.

2. Simulated Kalman Filter Algorithm

The simulated Kalman filter (SKF) algorithm is illustrated in Figure-1(a). Consider *n* number of agents, SKF algorithm begins with initialization of *n* agents, in which the states of each agent are given randomly. The maximum number of iterations, t_{max}, is defined. The initial value of error covariance estimate, $P(0)$, the process noise value, Q, and the measurement noise value, R, which are required in Kalman filtering, are also defined during initialization stage. Then, every agent is subjected to fitness evaluation to produce initial solutions. The fitness values are compared and the agent having the best fitness value at every iteration is registered as $\boldsymbol{X}_{\mathbf{best}}$. The-best-so-far solution in SKF is named as $\boldsymbol{X}_{\mathbf{true}}$. The $\boldsymbol{X}_{\mathbf{true}}$ is updated only if the $\boldsymbol{X}_{\mathbf{best}}(t)$ is better than the $\boldsymbol{X}_{\mathbf{true}}$. The subsequent calculations are largely similar to the predict-measure-estimate steps in Kalman filter. Finally, the next iteration is executed until the maximum number of iterations, t_{max}, is reached.

3. Particle Swarm Optimization

The particle swarm optimization (PSO) is illustrated in Figure-3. Consider *n* number of particle, PSO begins with initialization of *n* particles, in which the coordinates of *i*th particle, $x_i(0)$, are given randomly. The maximum number of iterations, t_{max}, and initial velocity of *i*th particle, $\boldsymbol{v}_i(0)$, are also defined during the initialization. Then, every particle is subjected to fitness evaluation to produce initial solutions. Personal best, *pbest*, and global best, *gbest*, are updated. After that, the velocity and position are updated. Lastly, the next iteration is executed until the maximum number of iterations, t_{max}, is reached.

4. Hybrid SKF-PSO Algorithm

Note that even though the SKF follows predict-measure-estimate steps as in Kalman filter, the states are not updated during the predict step. Hence, in the proposed hybrid SKF-PSO algorithm, PSO is employed as the prediction operator in SKF. In this study, four different approaches to employ PSO as the prediction operator are investigated.

A. *Hybrid SKF with PSO: PSO as prediction Operator (Model-1)*

In this approach, the velocity is updated and next position is predicted according to the rule of PSO. It is applied to each particle as a prediction operator to the original SKF algorithm. The hybrid SKF-PSO (PSO as prediction operator) algorithm is shown in Figure-2.

B. *Hybrid SKF-PSO: PSO as Prediction operator when better solution is found (Model-2)*

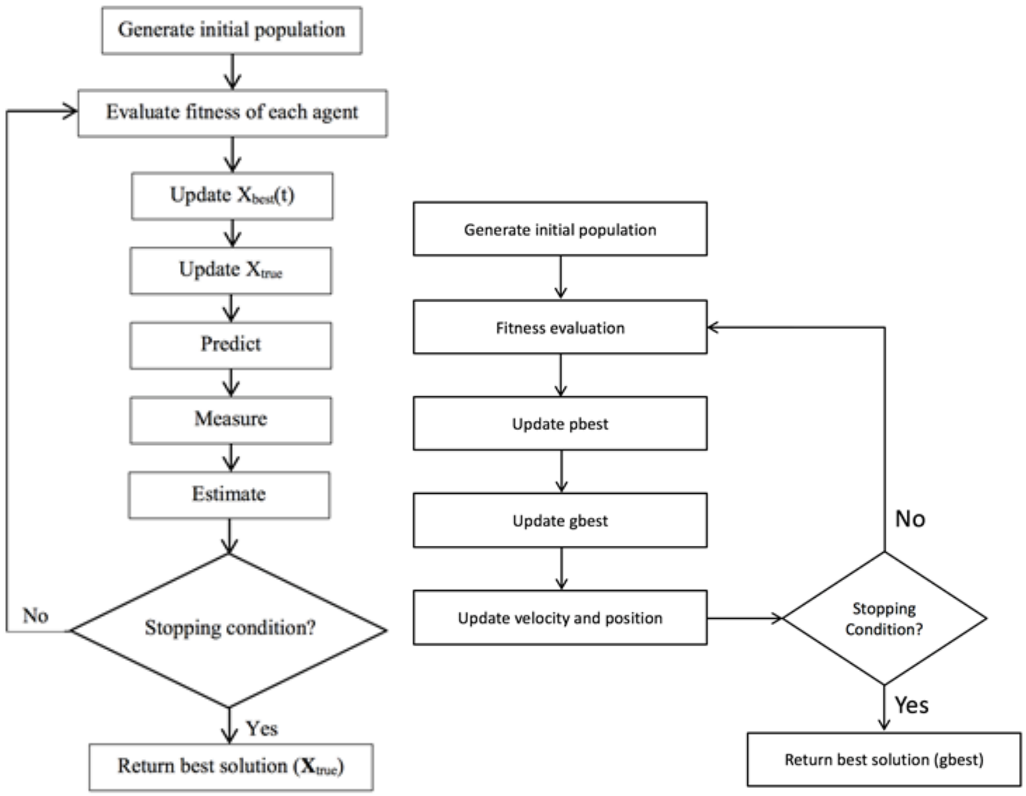
In this second approach, the velocity is updated and next position is predicted only if a better solution compared to existing position is found. The hybrid SKF-PSO (PSO as prediction operator when better solution is found) algorithm is shown in Figure-3.

C. *Hybrid SKF-PSO: PSO as Prediction operator with Jumping Rate (Model-3)*

In this third approach, an additional variable is introduced in hybrid SKF-PSO, which is the jumping rate, J_r, that is a predefined constant in the range of [0,1]. Prediction based on PSO is performed if jumping rate condition is satisfied. Once jumping rate condition is satisfied, the velocity is updated and next position is predicted. The hybrid SKF-PSO (PSO as prediction operator with jumping rate) algorithm is shown in Figure-4.

D. *Hybrid SKF-PSO: PSO as Prediction operator with Jumping Rate and when better solution is found (Model-4)*

An additional variable is introduced in hybrid SKF-PSO, which is the jumping rate, J_r, that is a predefined constant in the range of [0,1]. Prediction based on PSO is performed if jumping rate condition is satisfied. Once jumping rate condition is satisfied, fitness evaluation is performed again after the velocity is updated and next position is predicted. Then, agents move to the predicted position if better solution is found at the predicted position. The hybrid SKF-PSO (PSO as prediction operator with jumping rate and when better solution is found) algorithm is shown in Figure-5.



(a) (b)

Figure 1: (a) The simulated Kalman filter (SKF) algorithm (b) The Particle Swarm Optimization (PSO)

5. EXPERIMENTS

The CEC2014 benchmark functions [9] have been employed for performance evaluation of the newly proposed algorithms. Thirty functions are available, which consist of 3 unimodal functions, 13 multimodal functions, 6 hybrid functions, and 8 composition functions, as shown in Table-1. Table-2 shows the setting parameters used in Hybrid SKF-PSO experiment including SKF parameters. The search space for all the test functions is [-100,100] for all dimensions.

6. RESULTS AND DISCUSSION

The experimental result in terms of averaged values for CEC2014 benchmark functions are tabulated in Table-3. Result in bold represent the best performance. To rank the result, Friedman test method is used. The result in Table-4 shows that, the hybrid SKF-GSA (Model-3) and Hybrid SKF-GSA (Model-4) are ranked higher compared to original SKF algorithm.

Based on the averaged performances, Wilcoxon signed rank test is performed and the result is tabulated in Table-5. The level of significant chosen here is $\sigma = 0.05$. It is found that statistically, the newly proposed SKF-PSO (Model-3) is significantly superior to the original SKF in solving continuous numerical optimization problems.

7. CONCLUSION

The primary objective of this study is to perform performance evaluation of the 4 newly introduced hybrid SKF-PSO algorithm. The findings show that our new Hybrid SKF-PSO (Model-3) is statistically significant compared to the original SKF algorithm

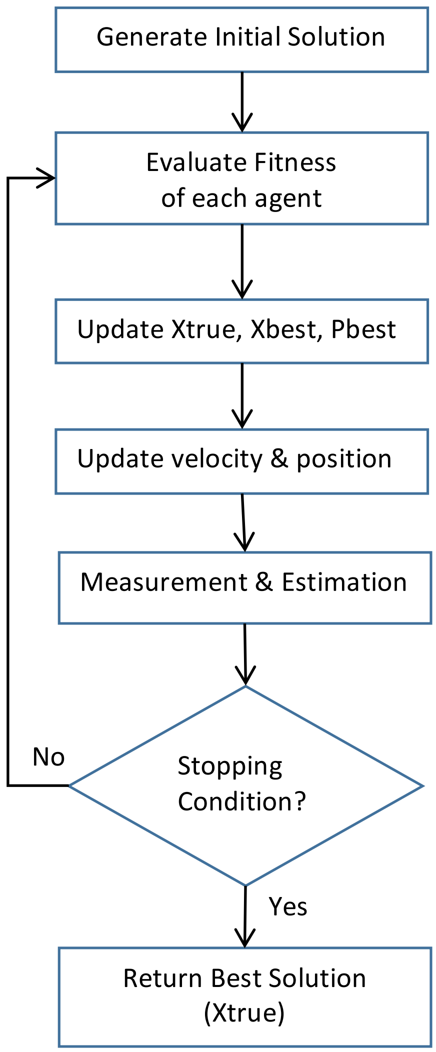


Figure 2: The computational model 1

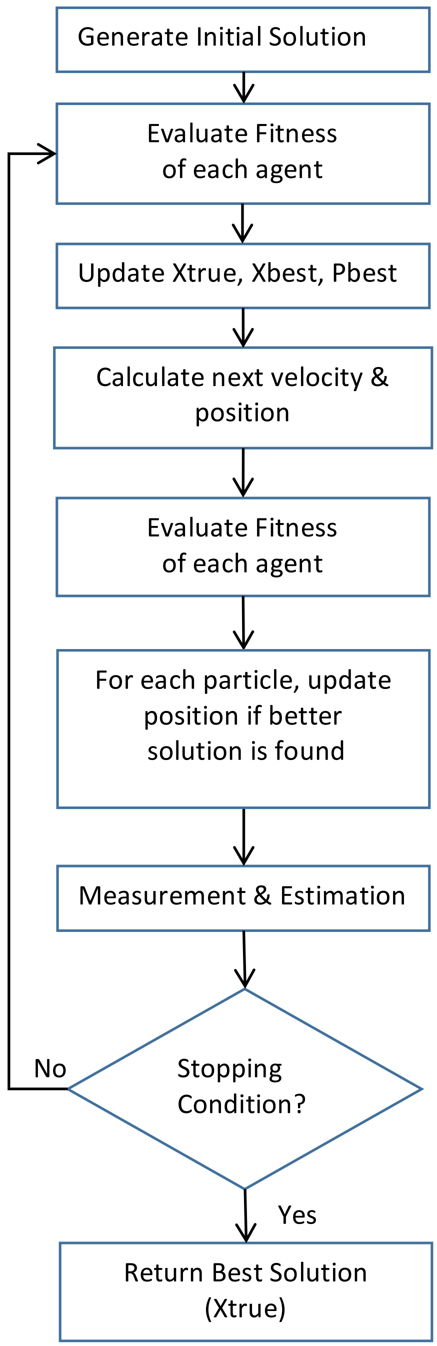


Figure 3: The computational model 2

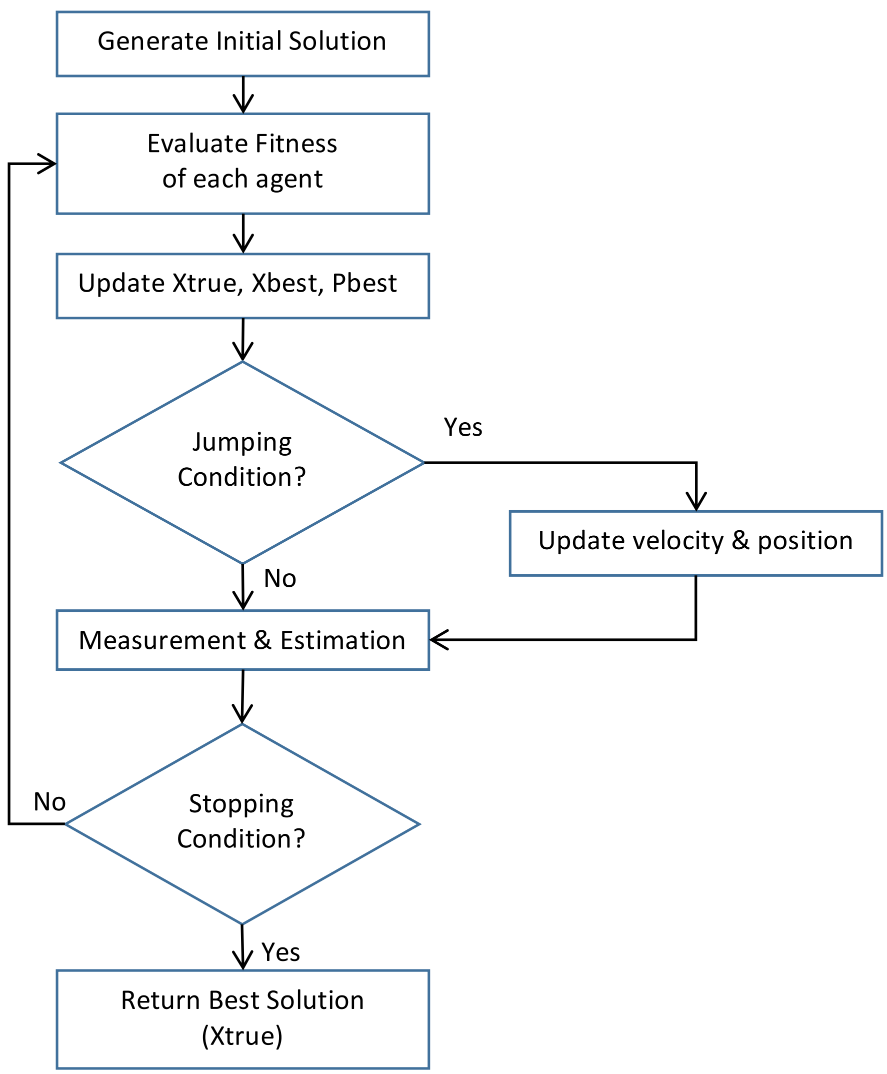


Figure 4: The computational model 3

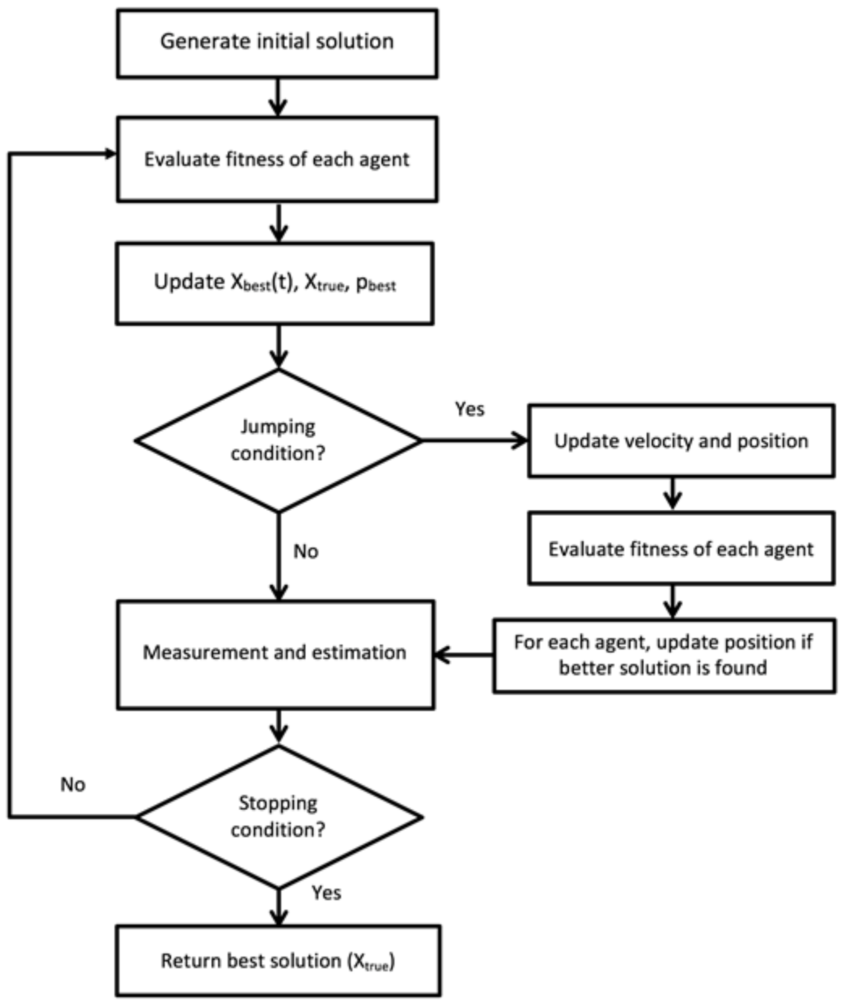


Figure 5: The computational model 4

Table 1: The CEC2014 benchmark problems.

Function ID	Type	Ideal Fitness
F1	Unimodal	100
F2		200
F3		300
F4	Multimodal	400
F5		500
F6		600
F7		700
F8		800
F9		900
F10		1000
F11		1100
F12		1200
F13		1300
F14		1400
F15		1500
F16		1600
F17	Hybrid	1700
F18		1800
F19		1900
F20		2000
F21		2100
F22		2200
F23	Composition	2300
F24		2400
F25		2500
F26		2600
F27		2700
F28		2800
F29		2900
F30		3000

Table 2: Setting parameters for Hybrid SKF-PSO.

Experimental Parameters	
Number of agent	100
Number of dimension	50
Number of run	50
Number of iteration	10,000
Search space	[-100.100]
rand	[-1,1]
SKF Parameters	
Error covariance estimate, *P*	1000
Process noise, *Q*	0.5
Measurement noise, *R*	0.5
PSO Parameters	
ω_{max}	0.9
ω_{min}	0.1
Cognitive coefficient, c_1	2
Social coefficient, c_2	2
SKF-PSO Parameters	
Jumping rate, J_r	0.2

Table 3: The average fitness value obtained by SKF, SKF-PSO (Model-1), SKF-PSO (Model-2), SKF-PSO (Model-3), and SKF-PSO (Model-4). Numbers in bold indicate the best fitness.

Function	SKF	SKF-PSO (MODEL-1)	SKF-PSO (MODEL-2)	SKF-PSO (MODEL-3)	SKF-PSO (MODEL-4)
F1	**4702013.17**	94642657.63	7485558	9190373	8040916
F2	24498691.7	128169629.1	3361.991	1653467	**2499.413**
F3	18147.7005	22204.49728	**5400.831**	6766.293	10197.71
F4	**532.77148**	1447.603694	582.437	642.6912	564.0094
F5	**520.010016**	521.0380178	521.0924	520.0467	520.022
F6	633.441686	631.7937166	632.6218	**625.8339**	631.5916
F7	700.246225	700.1206971	**700.0328**	700.9502	700.037
F8	807.981323	853.0536415	**801.194**	824.6129	804.0395
F9	1059.13877	1062.437812	1053.9	**1050.618**	1060.904
F10	1335.18324	1579.77401	**1157.123**	1278.715	1341.456
F11	6249.36725	13412.69654	6086.102	**5808.529**	6175.303
F12	1200.23641	1202.479962	1203.003	**1200.149**	1200.293
F13	1300.55973	1300.621589	**1300.559**	1300.593	1300.564
F14	1400.30009	1400.369487	1400.304	**1400.268**	1400.308
F15	1551.6584	1534.043637	1537.349	**1524.813**	1546.723
F16	1619.12553	1621.925586	1622.221	**1618.265**	1618.914
F17	908272.092	6286354.919	4093009	**796747.1**	8591204
F18	6941389.77	85131.98555	25199.36	**2466.73**	2987.862
F19	1950.223	1964.527028	**1933.611**	1946.369	1937.8
F20	34799.058	10634.96951	3157.536	**3018.307**	7585.159
F21	1186640.91	1073502.953	320294.1	**348777**	242007.8
F22	3429.10583	3511.708839	3394.301	**3337.167**	3378.551
F23	2645.68902	2666.833461	2646.646	2647.005	**2645.491**
F24	2667.24977	2673.073218	2661.464	**2657.402**	2664.494
F25	2730.40182	2731.467837	**2724.178**	2726.652	2724.693
F26	2766.38525	**2700.547515**	2759.11	2776.515	2733.87
F27	3883.3415	3863.798829	4779.875	**3709.012**	4183.174
F28	7223.36965	10325.0302	11437.62	**6688.577**	9891.017
F29	5997.83017	9350.688913	478667.6	**4092.679**	375658.3
F30	**19753.2888**	249763.1993	2542082	43411.62	505305.3

Table 4: Friedment test result.

Algorithm	Ranking	Score
Hybrid SKF-PSO (MODEL-3)	1	2.2000
Hybrid SKF-PSO (MODEL-4)	2	2.7666

Hybrid SKF-PSO (MODEL-2)	3	2.8000
Original SKF	4	3.1333
Hybrid SKF-PSO(MODEL-1)	5	4.1333

Table 5: Wilcoxon test result.

Comparison	**R^-**	**R^+**
Hybrid SKF-PSO(MODEL-1) vs SKF	127	338
Hybrid SKF-PSO(MODEL-2) vs SKF	274	191
Hybrid SKF-PSO(MODEL-3) vs SKF	351	114
Hybrid SKF-PSO(MODEL-4) vs SKF	271	194

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