Four Different Methods to Hybrid Simulated Kalman Filter (SKF) with Gravitational Search Algorithm (GSA)

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Abstract—This paper presents a performance evaluation of a new hybrid Simulated Kalman Filter and Gravitational Algorithm (SKF-GSA), 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 Newtonian gravitational law, gravitational search algorithm (GSA) has been introduced in 2009. Four methods (models) to hybridize SKF and GSA are proposed in this paper. The performance of the hybrid SKF-GSA 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 gravitational search algorithm (GSA) [2] are examples of population-based optimization algorithms.

In literature, GSA has been subjected to various improvements including hybridization with other optimization algorithms. For example, GSA can be hybridized with particle swarm optimization [3], genetic algorithm [4], cuckoo search [5], chaos [6], and artificial bee colony [7]. SKF has been applied to solve various optimization problems [8]–[11]. In this study, hybridization between SKF with GSA is proposed. Specifically, 4 different methods to hybrid SKF with GSA 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. Gravitational Search Algorithm

In GSA, agents are considered as an object and their performance are expressed by their masses. The position of particle is corresponding to the solution of the problem. According to law of motion, the current velocity of any mass is equal to the sum of the fraction of its previous velocity and the variation in the velocity. Acceleration of any mass is equal to the force acted on the system divided by mass of inertia. In summary, the algorithm of standard GSA is shown in Figure-1(b).

4. Hybrid SKF-GSA 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-GSA algorithm, GSA is employed as the prediction operator in SKF. In this study, four different approaches to employ GSA as the prediction operator are investigated.

A. Hybrid SKF with GSA: GSA as prediction Operator (Model 1)

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

B. Hybrid SKF-GSA: GSA 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-GSA (GSA as prediction operator when better solution is found) algorithm is shown in Figure-3

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

In the third approach, an additional variable is introduced in hybrid SKF-GSA, which is the jumping rate, J_r, that is a predefined constant in the range of [0,1]. Prediction based on GSA 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-GSA (GSA as prediction operator with jumping rate) algorithm is shown in Figure-4.

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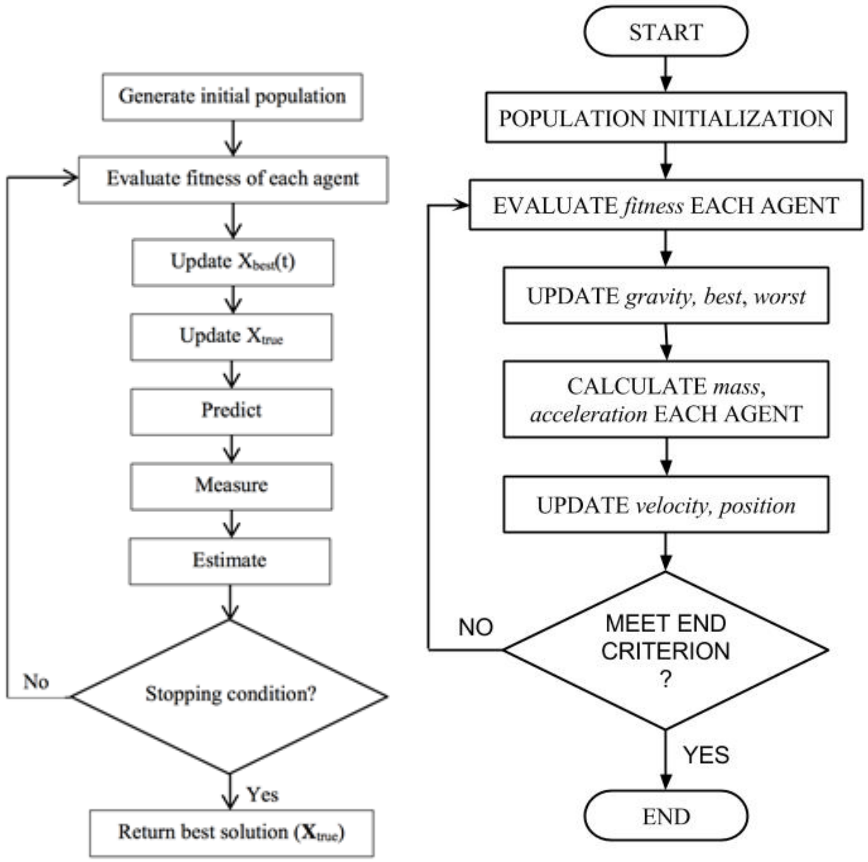

(a) (b)

Figure 1: (a) The simulated Kalman filter (SKF) algorithm (b) The gravitational search algorithm (GSA)

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

An additional variable is introduced in hybrid SKF-GSA, which is the jumping rate, J_r, that is a predefined constant in the range of [0,1]. Prediction based on GSA 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-GSA (GSA as prediction operator with Jumping Rate and when better solution is found) algorithm is shown in Figure-5.

5. EXPERIMENTS

The CEC2014 benchmark functions (http://www.ntu.edu.sg/home/EPNSugan/index_files/CEC2014) 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.

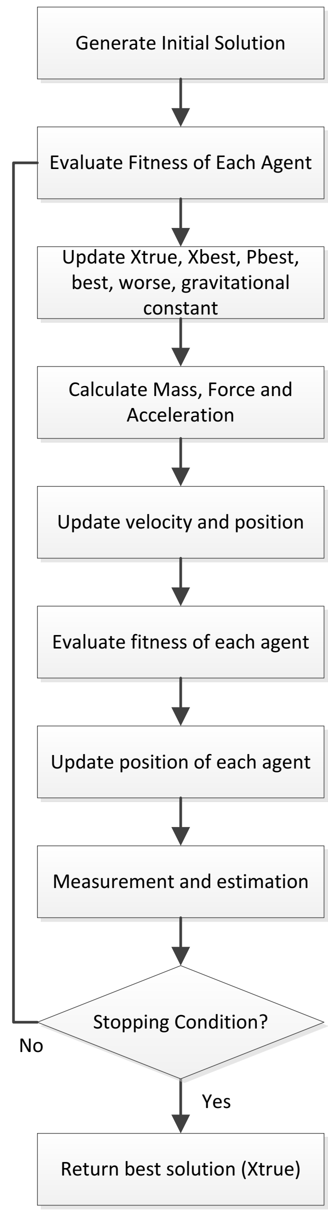

Figure 2: The computational model 1.

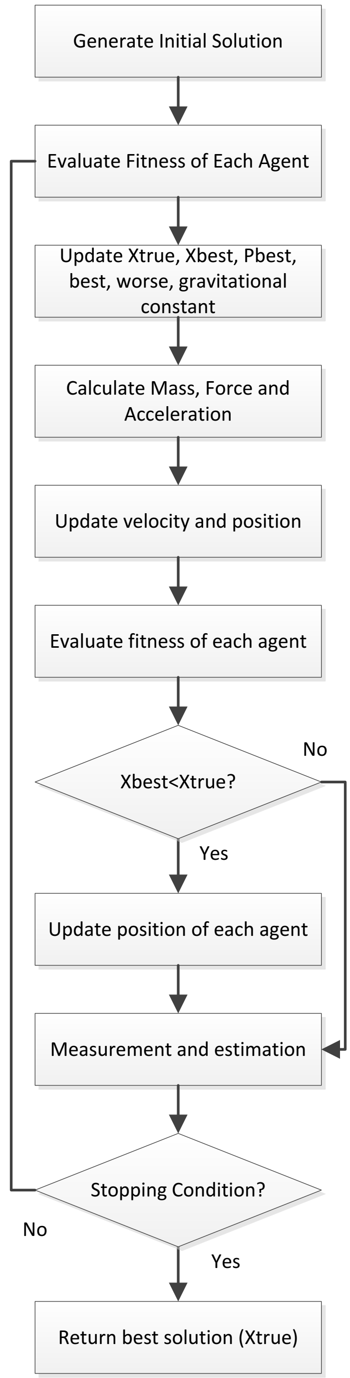

Figure 3: The computational model 2.

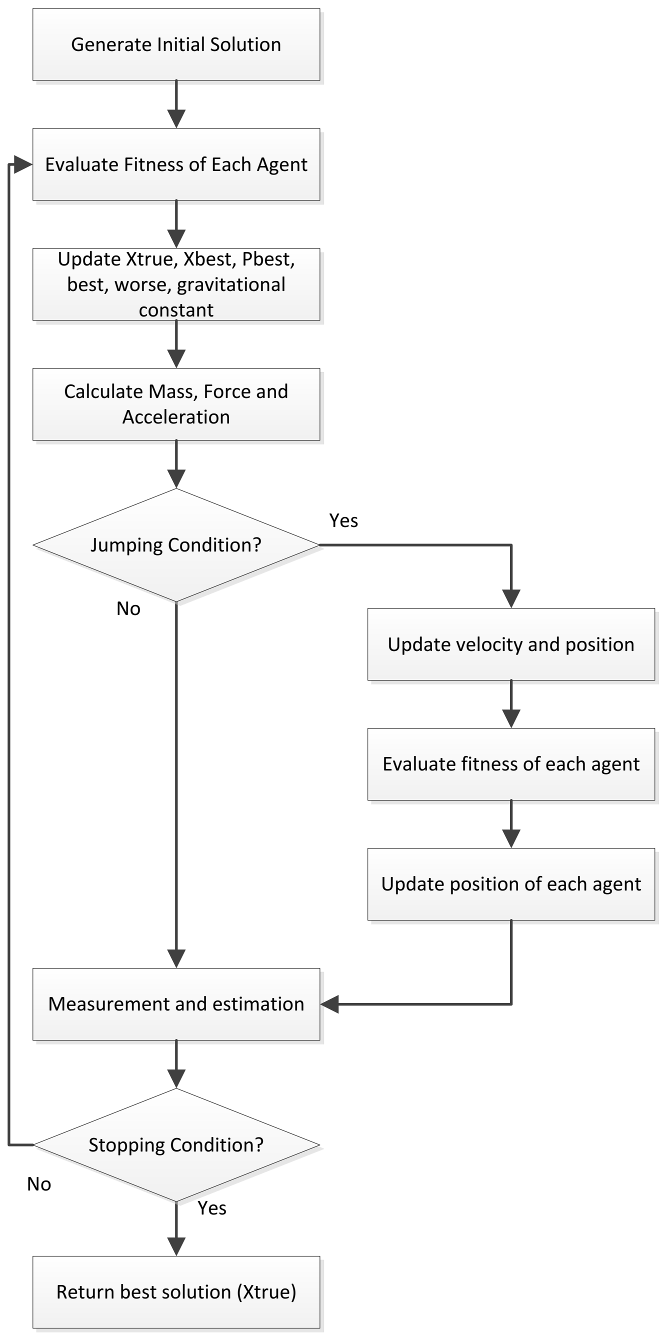

Figure 4: The computational model 3.

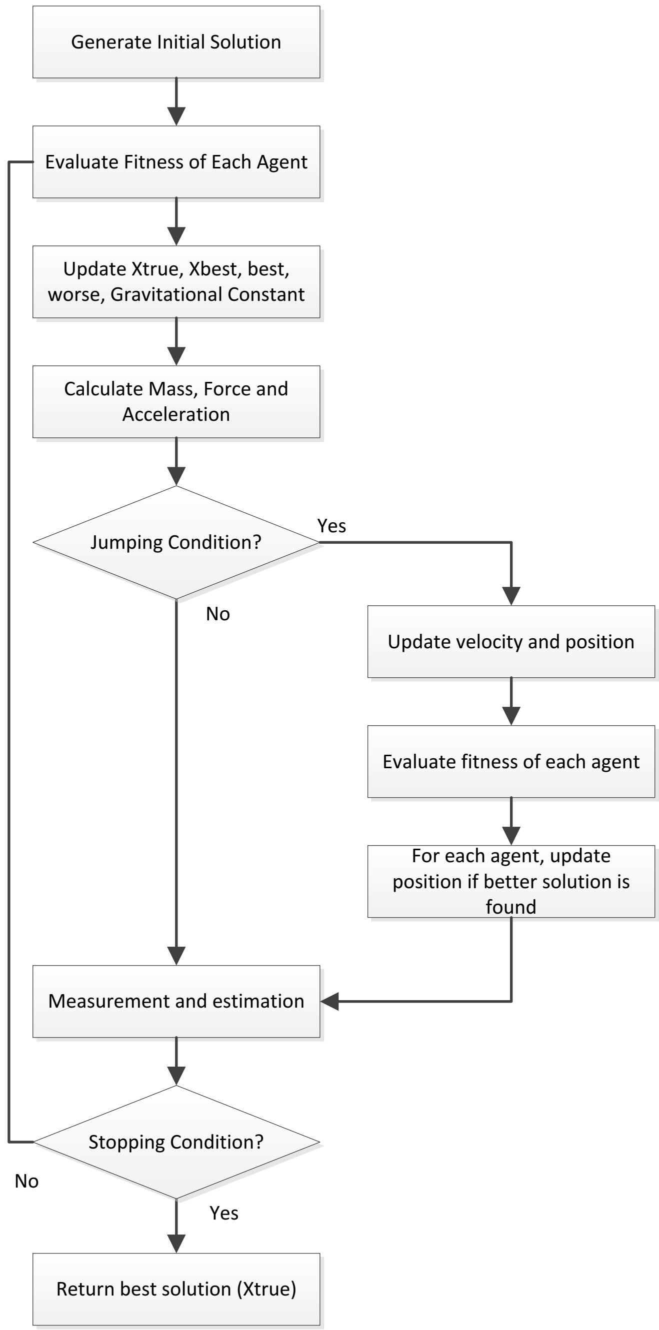

Figure 5: The computational model 4.

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.

7. CONCLUSION

The primary objective of this study is to perform performance evaluation of the 4 newly introduced hybrid SKF-GSA algorithm. The findings show that our new Hybrid SKF-GSA (Model-3) and Hybrid SKF-GSA (Model-4) rank higher compare to their original SKF algorithm.

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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-GSA.

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
GSA Parameters	
α	20
G_o	100
SKF-GSA Parameters	
Jumping rate, J_r	0.1

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

Function	SKF	SKF-GSA (MODEL-1)	SKF-GSA (MODEL-2)	SKF-GSA (MODEL-3)	SKF-GSA (MODEL-4)
F1	4702013.17	51854702.7	26328680	**4090337**	21544003
F2	24498691.7	118126837.8	2.69E+08	**2881.989**	3445.137
F3	18147.7005	11654.18785	**5484.572**	15126.87	16314.78
F4	**532.77148**	842.9557788	1108.239	546.5491	696.7924
F5	520.010016	**519.9998939**	520	520	520
F6	633.441686	630.3217047	635.2618	**629.0965**	630.5952
F7	700.246225	**700**	700.0098	700.0134	700.0079
F8	**807.981323**	978.0772821	854.4043	817.2372	821.71
F9	**1059.13877**	1132.321694	1109.717	1059.352	1065.489
F10	**1335.18324**	5958.468836	1719	1603.906	1563.484
F11	**6249.36725**	7266.849433	6922.997	6399.52	6291.384
F12	1200.23641	**1200.001825**	1200.132	1200.056	1200.242
F13	1300.55973	**1300.449135**	1300.498	1300.528	1300.526
F14	1400.30009	1400.318894	1400.311	**1400.291**	1400.295
F15	1551.6584	1521.944693	**1508.694**	1542.934	1540.791
F16	1619.12553	1621.993276	1620.065	1619.134	**1619.103**
F17	908272.092	6707392.848	9902591	**828708.5**	1099232
F18	6941389.77	82385996.81	1.16E+08	**36723.44**	2479174
F19	1950.223	1957.82565	**1942.455**	1947.332	1943.598
F20	34799.058	21161.83925	**7579.507**	23341.79	26902.73
F21	1186640.91	196751.8183	**127091.6**	1052250	1061867
F22	3429.10583	3954.785951	3716.958	3375.371	**3296.479**
F23	2645.68902	2655.390989	2676.623	**2644.525**	2648.265
F24	2667.24977	2660.206042	**2659.96**	2662.138	2661.314
F25	2730.40182	2731.007318	**2729.851**	2731.905	2731.957
F26	**2766.38525**	2794.426704	2796.266	2782.365	2782.335
F27	3883.3415	4073.982497	3898.514	**3755.537**	3798.4
F28	**7223.36965**	9768.77567	8993.911	7803.023	7573.027
F29	5997.83017	91266814.62	173552251.4	**4203.397**	4248.279
F30	**19753.2888**	1617400.197	1700541.665	20466.75	70348

Table 4: Friedment test result.

Algorithm	Ranking	Score
Hybrid SKF-GSA (MODEL-3)	1	2.3667
Hybrid SKF-GSA (MODEL-4)	2	2.7667
Original SKF	3	2.9333
Hybrid SKF-GSA (MODEL-2)	4	3.4000
Hybrid SKF-GSA (MODEL-1)	5	3.5333