Performance Evaluation of Hybrid SKF Algorithms: Hybrid SKF-PSO and Hybrid SKF-GSA

Badaruddin Muhammad, Zuwairie Ibrahim, Kamil Zakwan Mohd Azmi
Faculty of Electrical and Electronics Engineering
Universiti Malaysia Pahang
26600 Pekan, Malaysia

Khairul Hamimah Abas
Faculty of Electrical Engineering
Universiti Teknologi Malaysia
81310 Skudai, Johor, Malaysia

Nor Azlina Ab Aziz, Nor Hidayati Abd Aziz
Faculty of Engineering and Technology
Multimedia University,
75450 Melaka, Malaysia

Mohd Saberi Mohamad
Faculty of Computing,
Universiti Teknologi Malaysia
81310 Johor, Malaysia

Abstract—This paper presents a performance evaluation of hybrid Simulated Kalman Filter Gravitational Algorithm (SKF-GSA), and hybrid Simulated Kalman Filter 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. The performance of the hybrid algorithms (SKF-GSA and SKF-PSO) is compared using CEC2014 benchmark dataset for continuous numerical optimization problems. Based on the analysis of experimental results, we found that the SKF-PSO performs the best among all.

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), gravitational search algorithm (GSA) and Particle Swarm Optimization are examples of population-based optimization algorithms. GSA has been introduced in 2009 by Rashedi *et al*. [1], whereby, PSO has been introduced earlier in 1994 by Eberhart and Kennedy [2], while SKF has been recently introduced by Ibrahim *et al.* [3] in 2015. Even though all these three algorithms are population-based, however, they are inspired differently. In particular, GSA is inspired by Newtonian law of gravity and law of motion, PSO is inspired by bird flocking behavior, while SKF is inspired by the estimation capability of Kalman filter. SKF has been applied to solve various optimization problems [4-8]. Recently, the hybrid of SKF with PSO and GSA have been presented [9-10]. In this paper, the performance of both hybrid algorithms are investigated.

2. SIMULATED KALMAN FILTER ALGORITHM

The simulated Kalman filter (SKF) algorithm is SKF is illustrated in Figure-1. 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 [7], 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-2.

4. 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 ith particle, $x_i(0)$, are given randomly. The maximum number of iterations, t_{max}, and initial velocity of ith 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.

5. 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. 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. Then, fitness evaluation is performed again after the velocity is updated and next position is predicted. After that, agents move to the predicted position if better solution is found at the predicted position. The hybrid SKF-GSA algorithm is shown in Figure-4.

In detail, the hybrid SKF-GSA algorithm begins with initialization of n agents, in which the states of each agent are given randomly. The maximum number of iterations, t_{max}, the initial value of error covariance estimate, $P(0)$, the process noise value, Q, the measurement noise value, R, and jumping rate value, J_r, are also defined during initialization stage. Then, every agent is subjected to fitness evaluation to produce initial solutions. After that, $\boldsymbol{X}_{\mathbf{best}}(t)$ and $\boldsymbol{X}_{\mathbf{true}}$ are updated according to SKF algorithm and *pbest* is updated according to GSA algorithm. In hybrid SKF-GSA, the purpose of jumping rate, J_r, is to control the occurrence of the prediction. Based on our observation, the performance of SKF cannot be enhanced when GSA is executed at every iteration as the prediction operator of SKF. For the position update, agent moves to a new position only if the fitness of the new position is better than the fitness of the current position. The algorithm continues with measurement and estimation similar to SKF. The next iteration is executed until the maximum number of iterations, t_{max}, is reached.

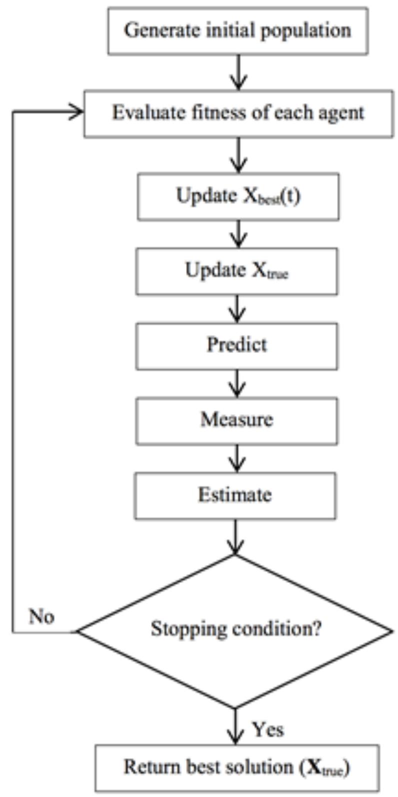

Figure 1: The simulated Kalman filter (SKF) algorithm

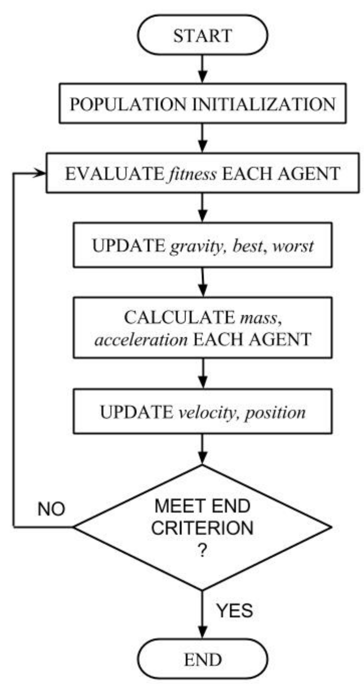

Figure 2: The gravitational search algorithm (GSA)

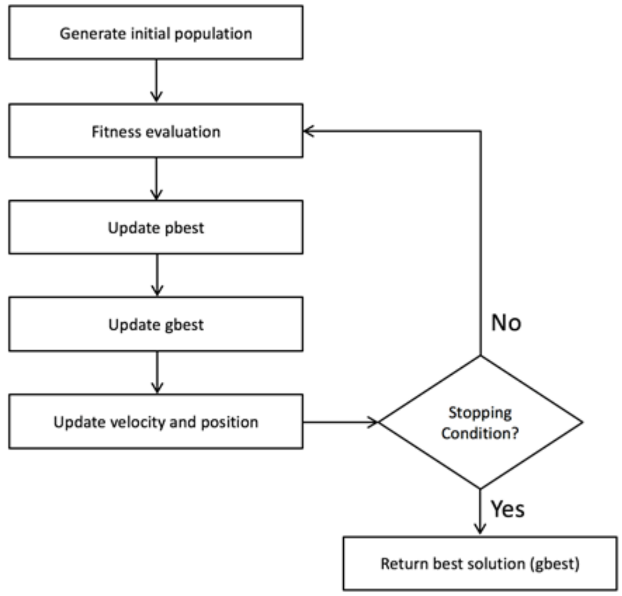

Figure 3: The particle swarm optimization (PSO) algorithm.

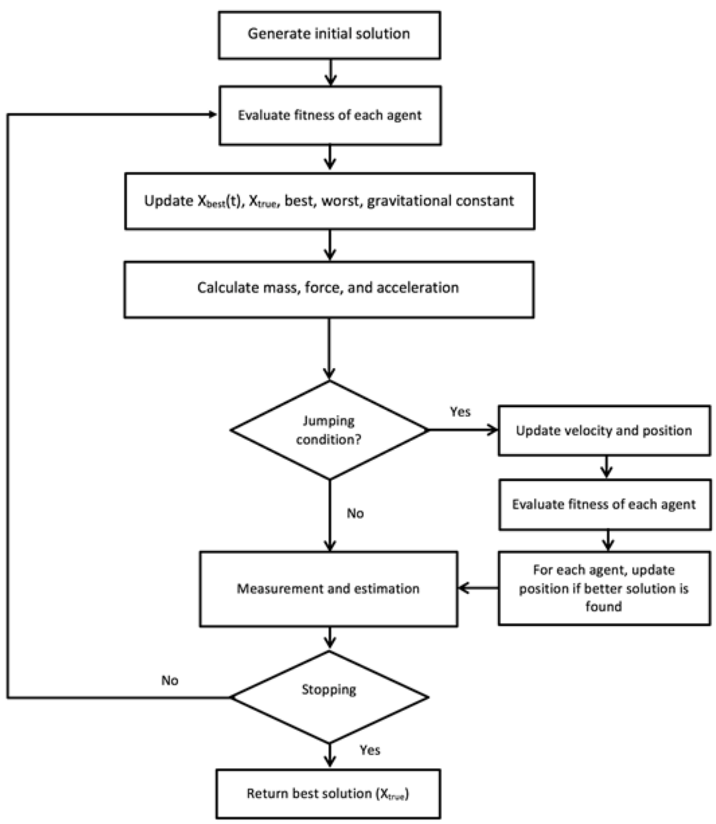

Figure 4: The new hybrid SKF-GSA algorithm.

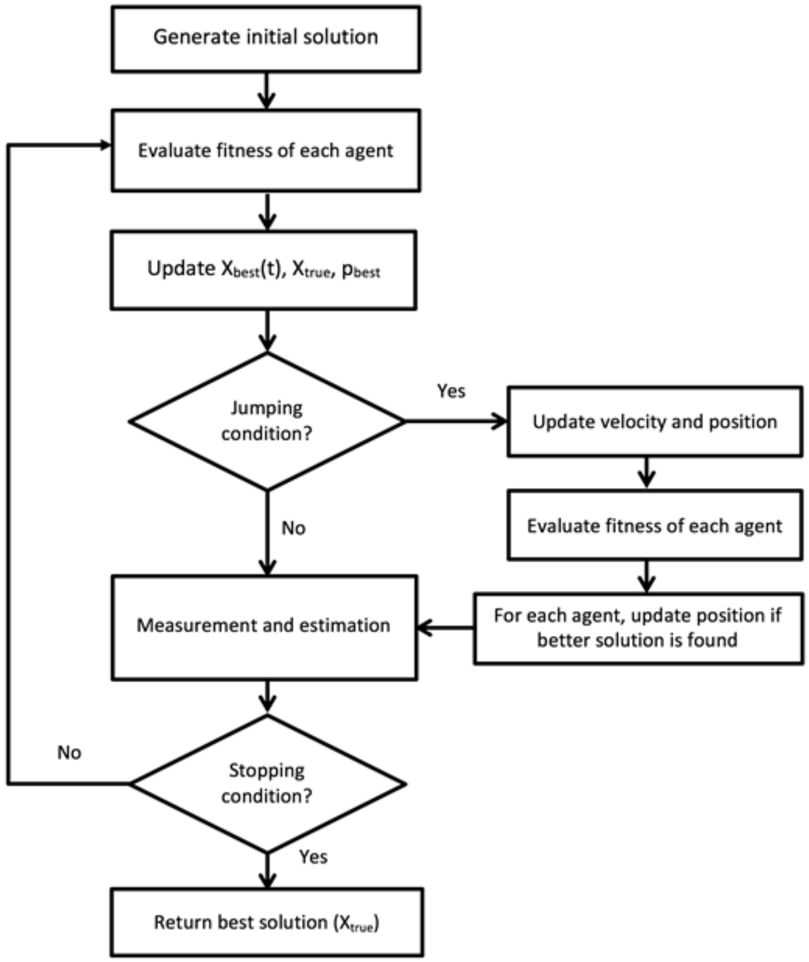

Figure 5: The new hybrid SKF-PSO algorithm

6. 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. 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 algorithm is shown in Figure-5.

In detail, the hybrid SKF-PSO algorithm begins with initialization of n agents, in which the states of each agent are given randomly. The maximum number of iterations, t_{max}, the initial value of error covariance estimate, $P(0)$, the process noise value, Q, the measurement noise value, R, and jumping rate value, J_r, are also defined during initialization stage. Then, every agent is subjected to fitness evaluation to produce initial solutions. After that, $\boldsymbol{X}_{\mathbf{best}}(t)$ and $\boldsymbol{X}_{\mathbf{true}}$ are updated according to SKF algorithm and *pbest* is updated according to PSO algorithm.

Similar with hybrid SKF-GSA, the purpose of jumping rate, J_r, in hybrid SKF-PSO is to control the occurrence of the prediction. This is due to the same reason that is the performance of SKF cannot be enhanced when PSO is executed at every iteration as the prediction operator of SKF. The velocity update in hybrid SKF-PSO is almost similar to PSO. The only different is that the *gbest* is replaced with $\boldsymbol{X}_{\mathbf{true}}$. For the position update, agent moves to a new position only if the fitness of the new position is better than the fitness of the current position. Thus, pre-calculation of next position, which is called $\boldsymbol{X}_{\mathbf{predict}}$, is required. The algorithm continues with measurement and estimation similar to SKF. The next iteration is executed until the maximum number of iterations, t_{max}, is reached.

7. EXPERIMENTS, RESULT, AND DISCUSSION

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 and Table-3 show the experimental setting parameters of SKF-GSA and SKF-PSO. The search space for all the test functions is [-100,100] for all dimensions.

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	2000
Search space	[-100.100]
rand	[-1,1]
SKF Parameters	
Error covariance estimate, P	1000
Process noise value, Q	0.5
Measurement noise value, R	0.5
GSA Parameters	
α	20
Initial gravitational constant, G_o	100
SKF-GSA Parameters	
Jumping rate, J_r	0.5

Table 3: Setting parameters for Hybrid SKF-PSO.

Experimental Parameters	
Number of agent	100
Number of dimension	50
Number of run	50
Number of iteration	2000
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 4: The average fitness value obtained by SKF, GSA, PSO, hybrid SKF-GSA, and hybrid SKF-PSO algorithms. Numbers in bold indicate the best fitness.

Function	SKF	GSA	PSO	SKF-GSA	SKF-PSO
F1	17369877	69127759	44394120	**3276982**	14888457
F2	18365308	123246207	25530051	16476.178	**9308.25**
F3	16118.04	138080.2	28696.06	**11472.418**	15192.94
F4	626.23	878.73471	836.66	**594.95572**	620.7
F5	520.01	**519.99972**	521.1	520.30496	520.06
F6	631.96	647.95535	633.5	632.53064	**631.19**
F7	701.26	702.09712	**700.01**	700.05063	700.09
F8	822.54	1076.4981	894.84	829.69389	**819.01**
F9	1059.57	1250.6996	1076.7	**1059.2212**	1060.54
F10	1426.18	8193.1666	2372.9	1461.6072	**1386.46**
F11	6203.75	9275.6875	12218.77	6442.8536	**6075.93**
F12	1200.25	**1200.0029**	1202.94	1200.6481	1200.54
F13	1300.56	**1300.4779**	1300.57	1300.5885	1300.53
F14	1400.3	**1400.2984**	1400.38	1400.3026	1400.3
F15	1556.67	1765.9041	**1531**	1554.3769	1534.9
F16	**1619.43**	1622.5232	1622.04	1619.5755	1619.51
F17	2816604.7	2181643.8	3477529.1	**487245.9**	1833023
F18	8997221.5	69338904	277318.63	**2800.56**	14744
F19	1958.34	**1944.0205**	1960.5	1949.6665	1946.8
F20	35668.02	59215.961	18579.12	**9150.1518**	13214.16
F21	3111583	1844950.4	859993.75	**99768.265**	516879.54
F22	3473.36	4133.8618	**3264.9**	3456.4354	3352.37
F23	2649.31	**2500**	2654.93	2648.0845	2647.11
F24	2666.49	**2600.0934**	2676.79	2664.4695	2664.14
F25	2731.71	**2700**	2729.8	2729.3102	2720.8
F26	2792.91	2800.0814	**2700.54**	2728.3843	2735.52
F27	3905.2	4789.0123	3940.92	**3874.8081**	4352.18
F28	6934.64	6083.8872	6938.08	**5742.8773**	8847.23
F29	19573.46	**3100.1583**	4760.56	67265.516	379376.23
F30	25820.54	**3200.0124**	116075.51	25046.572	233143.69

Table 5: Wilcoxon test result.

Comparison	R^-	R^+
Hybrid SKF-PSO vs PSO	335	130
Hybrid SKF-PSO vs SKF	355	110
Hybrid SKF-GSA vs GSA	371	94
Hybrid SKF-GSA vs SKF	368	97

Table 6: Friedment test result.

Algorithm	Ranking	Score
Hybrid SKF-PSO	1	2.3833
Hybrid SKF-GSA	2	2.4000
SKF	3	3.1167
GSA	4	3.4333
PSO	5	3.6667

The experimental result for CEC2014 benchmark functions are tabulated in Table-4. Result in bold represent the best performance. It is found that the proposed hybrid SKF-GSA and hybrid SKF-PSO performed better than individual SKF, GSA, and PSO in most problems, especially on the unimodal and hybrid problems.

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 SKF-GSA and SKF-PSO is also significantly superior to SKF, GSA and PSO in solving continuous numerical optimization problems. To rank the result, Friedman test method is used. The result in table-6 shows that, both SKF-PSO and SKF-GSA rank higher compare to their original PSO, and GSA. However, SKF-PSO show the best performance among all.

8. Conclusion

The primary objective of this study is to perform performance evaluation of the newly introduced hybrid SKF-GSA and hybrid SKF-PSO algorithm. The findings proved that both algorithms are superior to their original SKF, GSA, and PSO algorithms. Also, the performance of SKF-PSO is better than SKF-GSA.

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