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Research paper

A Simulated Kalman Filter Optimizer with White Hole Operator

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Abstract

The simulated Kalman filter (SKF) is a population-based optimization algorithm that was developed based on a well-known estimator called Kalman filter. Meanwhile, a white hole operator has been recently introduced to prevent premature convergence in black hole algorithm (BHA). The computation of white hole operator begins by selecting the worst agent as the white hole with event horizon. If an agent is located within the event horizon of white hole, the agent is pushed by the white hole. In this study, the white hole operator is used to improve the effectiveness of the SKF optimizer. A comprehensive experiment is done to evaluate the proposed SKF with white hole operator (SKFWH).

Keywords: *Optimization; Simulated Kalman filter; White hole.*

1. Introduction

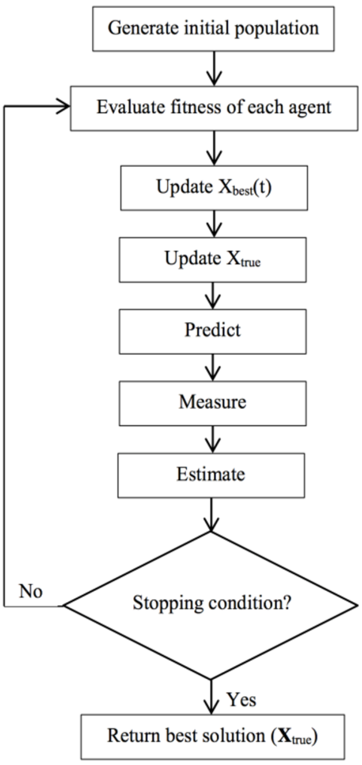
Recently, the use of a white hole operator to improve a black hole algorithm has been reported in literature [1-2]. The white hole operator was proposed to avoid the agents from exploring the area near the worst agent, which is also called the white hole agent. If an agent is located near the white hole agent, that agent is pushed away by the white hole agent.

On the other hand, the simulated Kalman filter (SKF) algorithm [3-4] is inspired by the estimation capability of Kalman filtering [5]. In SKF algorithm, every agent is regarded as a Kalman filter. Based on the mechanism of Kalman filtering and measurement process, every agent estimates the global minimum/maximum in a search space. To date, the SKF algorithm has been applied to solve several engineering problems. In signal processing, Adam *et al.* has employed angle-modulated SKF as feature selection in peak classification of EEG signal [6-7]. In telecommunication engineering, the SKF algorithm has been used as adaptive beamforming algorithm [8-11]. In industrial engineering, the SKF has been used to solve printed circuit board drill path optimization problem [12-13] and assembly sequence planning problem [14]. In scheduling application, the SKF has been employed in solving airport gate allocation problem [15-16]. In image processing, the SKF has been used as a template matching algorithm in distance measurement [17-18]. In system identification, the SKF algorithm has been used to estimate the model order and parameter value of an ARX model [19-20]. The SKF algorithm also has been introduced as a tuning method for proportional-integral-derivative (PID) controller [21]. Fundamentally, studies of the SKF algorithm have been reported [22-23]. Furthermore, modifications of the SKF [24-25] and hybridization with other algorithms [26-30] have been done to further improve the performance of the SKF algorithm. Several extensions of SKF algorithm for combinatorial optimization problems have also been introduced [31-34].

This paper presents a new improvement to SKF optimizer using the recently introduced white hole operator [35]. The effectiveness of the SKF optimizer with white hole operator is evaluated based on unimodal, multimodal, hybrid, and composite functions in CEC2014 benchmark test functions. Results show that the used of white hole operator significantly improves the SKF as global optimization algorithm.

2. The simulated Kalman filter optimizer

The simulated Kalman filter (SKF) algorithm is illustrated in Figure 1. Consider n number of agents, SKF algorithm begins with initialization of n agents randomly. The maximum number of iterations, t_{max}, the initial value of error covariance estimate, $P(0)$, the process noise covariance value, $Q \in [0, 1]$, and the measurement noise covariance value, $R \in [0, 1]$, are defined during the initialization stage. After the initialization, every agent is subjected to fitness evaluation to produce initial solutions $\{\boldsymbol{X}_1(0), \boldsymbol{X}_2(0), \boldsymbol{X}_3(0), \ldots, \boldsymbol{X}_{n-2}(0), \boldsymbol{X}_{n-1}(0), \boldsymbol{X}_n(0)\}$. The fitness values are compared and the agent having the best fitness value at every iteration, t, is registered as $\boldsymbol{X}_{best}(t)$. Subsequently, $\boldsymbol{X}_{true}$ is updated only if the $\boldsymbol{X}_{best}(t)$ is better than the $\boldsymbol{X}_{true}$. As shown in Figure 1, there are 6 important computations in the SKF algorithm.



Prediction

$$\boldsymbol{X}_i(t|t+1) = \boldsymbol{X}_i(t) \quad (1)$$

$$\boldsymbol{P}(t|t+1) = \boldsymbol{P}_i(t) + Q \quad (2)$$

where $\boldsymbol{X}_i(t)$ and $\boldsymbol{X}_i(t|t+1)$ denote the current state and current transition/predicted state, respectively, while the $\boldsymbol{P}_i(t)$ and $\boldsymbol{P}(t|t+1)$ denote the current error covariant estimate and current transition error covariant estimate, respectively.

Measurement

$$\boldsymbol{Z}_i(t) = \boldsymbol{X}_i(t|t+1) + \sin(2\pi r_i) \times |\boldsymbol{X}_i(t|t+1) - \boldsymbol{X}_{true}| \quad (3)$$

Estimate

$$K(t) = \frac{P(t|t+1)}{P(t|t+1)+R} \quad (4)$$

Then, the estimation of next state, $\boldsymbol{X}_i(t+1)$, and the updated error covariant, $P_i(t+1)$, are computed based on (5) and (6), respectively.

$$\boldsymbol{X}_i(t+1) = \boldsymbol{X}_i(t|t+1) + K(t) \times |\boldsymbol{Z}_i(t) - \boldsymbol{X}_i(t|t+1)| \quad (5)$$

$$P(t+1) = (1 - K(t)) \times P(t|t+1) \quad (6)$$

Fig. 1: The original simulated Kalman filter algorithm [3-4].

3. The white hole operator

If the black holes exist, then it should be possible to reverse the equations governing them to get the opposite of black hole, which is the white hole. As oppose to black hole agent in the black hole algorithm (BHA) [36], the white hole can be assigned to the worst agent in the population.
The white hole has its own event horizon as shown in Figure 2. The radius of the event horizon, R_{WH}, can be calculated based on the following equation:

$$R_{WH} = \frac{fit_{WH}}{\sum_{i=1}^{N} fit_i} \quad (7)$$

where fit_{WH} is the fitness value of the white hole, N is the number of agents, and fit_i is the fitness value of the i^{th} agent.
As shown in Figure 2(a), an arbitrary agent i may be positioned within the event horizon of the white hole. In this case, the agent is pushed by the white hole as illustrated in Figure 2(b). Due to this, the position of the agent i is updated as follows:

$$X_i(t+1) = X_i(t) + rand \times \left(X_{WH} + X_i(t)\right) \quad (8)$$

where $X_i(t+1)$ and $X_i(t)$ are the locations of the arbitrary agent i at iterations t+1 and t, respectively. The $rand$ is a random number belonging to [0,1] and X_{WH} is the location of the white hole agent. This white hole operator is computed after the measurement step in SKF algorithm as shown in Figure 3. Note that the white hole operator is applied only to the agent that is located within the event horizon of a white hole agent. Otherwise, the solution is updated using (5) as of the original SKF algorithm.

4. Experiment, Result, and Discussion

The CEC2014 Benchmark Test Suite for single-objective optimization [37] was employed to observe the performance of the SKF algorithm with white hole operator. This test suite comprises of 30 functions of minimization problem. The experiments were repeated for several runs and the mean fitness was calculated. In all experiments, $Q = R = 0.5$.
In the first experiment, the performance of the proposed SKFWH algorithm is compared with the performance of the original SKF algorithm. Using the CEC2014 functions, the problems' dimension can be adjusted. Therefore, 10-dimensions and 50-dimenstions test functions were tested. Obviously, 50-dimensions test functions are more difficult to solve than the 10-dimensions test functions. The optimization process involved 100 agents and it is stopped at 1,000,000th function evaluation. After 50 runs, the mean fitness was calculated as tabulated in Table 1 and Table 2.
To analyze the experimental result, Wilcoxon signed rank test [38] was used for pairwise non-parametric statistical analysis. The Wilcoxon test usually is used when the population cannot be assumed to be normally distributed or it can be used to compare two related samples, matched samples, or repeated measurements on a single sample to assess whether their population mean ranks differ. The null hypothesis for the test assumes that there is no significant difference between the mean values of test algorithm and competing algorithm while the alternative hypothesis tries to determine if there is a significant difference between those two algorithms using 5% ($\alpha = 0.5$) significance level. Since the number of samples is 30, the critical value for the test is equal to 137. The sum of ranks where the test algorithm outperforms a competing algorithm is denoted as R+ while the sum of ranks where the test algorithm is outperformed by the competing algorithm is denoted as R-. Hence, the test algorithm is better than the competing algorithm if R+ > R- and the competing algorithm is significantly better than the BH algorithm if R- value is less than the critical value.

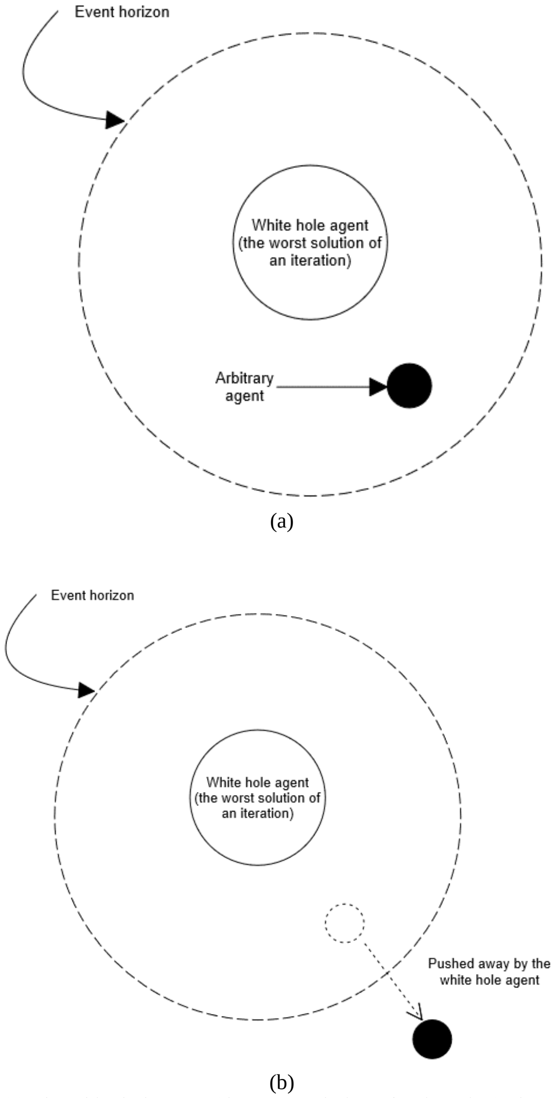


Fig. 2: The concept of white hole operator (a) The white hole agent (the worst solution of an iteration), the white hole's event horizon, and an arbitrary agent (located within the event horizon) are shown. (b) The agent located within the event horizon is pushed away by the white hole agent.

Based on Table 1 and Table 2, for the 10-dimensions problem, out of 30 functions, the SKFWH outperforms the original SKF in 27 test functions, while for the 50-dimensions problem, the SKFWH outperforms the original SKF in 21 test functions. Based on the Wilcoxon signed rank test results shown in Table 3 and Table 4, since R- < 137 (R- value is written in bold if it is less than 137), the proposed SKFWH outperforms the original SKF for both cases. This analysis indicates that the proposed SKFWH would performs significantly better than the original SKF in solving low and high dimensional problems.

For the second experiment, the number of agents of SKFWH were increased from 10 to 50 and finally to 100 while maintaining the number of function evaluations (*NFE*) as 1,000,000. The number of function evaluations can be calculated as *NFE* = *number of agents* × *number of iterations*. The number of dimensions in this experiment is 50. The mean fitness values are tabulated in Table 5. Based on the result of the Wilcoxon signed rank test in Table 6, since the critical value is 137, SKFWH with 50 agents performs significantly better than the SKFWH with 100 agents. R- value is written in bold if it is less than 137.

The third experiment investigates the importance of different initial values of error covariance estimate, $P(0)$, towards the performance of the SKFWH algorithm. The number of agents is 100, the number of iterations is 10,000, and the number of dimensions is 50. Several $P(0)$ values were investigated. Those values are 1, 10, 100, and 1,000. The mean fitness values are tabulated in Table 7. Based on the mean fitness values, the Wilcoxon signed ranked test was performed and the results are tabulated in Table 8. R- value is written in bold if it is less than 137. It is found that none of the pairwise tests show any significant difference. Hence, the initial values of error covariance estimate, $P(0)$, gives no impact to the performance of the SKFWH algorithm.

The last experiment investigates the performance of the SKFWH algorithm with different values of the number of agents, which are 10, 100, and 1000 agents. In this experiment, the number of iterations is 100 and the number of dimensions is 50. The mean fitness values are tabulated in Table 9. Based on the mean fitness values, the Wilcoxon signed ranked test was performed and the results are tabulated in Table 10. R- value is written in bold if it is less than 137. It is obvious that when the number of function evaluation is no longer a limit, significantly better results could be obtained when the number of agents is increased.

5. Conclusion

A lot of improvements of the SKF algorithms were reported in literature. However, this is the first time the SKF algorithm is improved using a new white hole operator. This white hole operator has been originally used to improve the black hole algorithm. In future, the usefulness of the white hole operator will be further investigated and tested to other optimization algorithm, such as finite impulse response optimizer [39].

Acknowledgement

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Table 1: The mean fitness based on 10-dimension test functions. Values in bold indicate smaller mean fitness.

Types	No.	SKFWH	SKF
Unimodal functions	1	**3912948.948**	5607771.528
	2	**1885.564735**	2672632.715
	3	**1718.212752**	3448.011551
Simple multimodal functions	4	**420.3010925**	420.91571
	5	**519.9999529**	520.0063855
	6	602.4705525	**601.9204931**
	7	**700.1624849**	1139329685566
	8	**800**	802.5417592
	9	**909.9052372**	913.3856203
	10	**1000.553511**	1121.796832
	11	**1405.400471**	1598.084375
	12	1200.080214	1200.122715
	13	**1300.241882**	1300.265143
	14	**1400.165654**	1400.329805
	15	**1501.204535**	1501.436656
	16	**1602.286956**	1602.519754
Hybrid functions	17	**137217.0239**	238934.7477
	18	10378.26401	**10225.36109**
	19	**1901.015338**	1901.262963
	20	**4420.818952**	7589.154424
	21	**4894.618402**	45650.08519
	22	**2211.437594**	2264.463448
Composition functions	23	**2622.868598**	2629.807706
	24	**2523.171623**	2525.825028
	25	**2670.516412**	2688.776931
	26	**2700.154528**	2700.189843
	27	**2772.816517**	2948.974324
	28	**3283.214765**	3308.24095
	29	**3253.417745**	72370.09974
	30	4247.948502	**4241.064993**

Table 2: The mean fitness based on 50-dimension test functions. Values in bold indicate smaller mean fitness.

Types	No.	SKFWH	SKF
Unimodal functions	1	**4599371.793**	4702013.172
	2	2584405.723	**24498691.66**
	3	**15654.3802**	18147.70046
Simple multimodal functions	4	**525.7442982**	532.7714796
	5	**520.0000447**	520.0100164
	6	**622.5405876**	633.4416857
	7	703.775289	**700.2462253**
	8	**804.4771155**	807.9813234
	9	1060.718543	**1059.138771**
	10	**1167.850431**	1335.183241
	11	6280.91523	**6249.367247**
	12	**1200.197155**	1200.236409
	13	1300.564131	**1300.55973**
	14	1400.315442	**1400.300086**
	15	**1550.736579**	1551.658399
	16	**1618.971832**	1619.125528
Hybrid functions	17	**815048.4382**	908272.092
	18	7320683.517	**6941389.773**
	19	**1941.608824**	1950.223
	20	**31143.98421**	34799.058
	21	**1140601.748**	1186640.91
	22	**3414.761688**	3429.105828
Composition functions	23	**2645.270911**	2645.689023
	24	**2661.797998**	2667.249774
	25	**2730.285585**	2730.401816
	26	2782.399055	**2766.385254**
	27	**3876.071383**	3883.341504
	28	**6834.144597**	7223.369647
	29	8049.657217	**5997.830166**
	30	**19708.47701**	19753.28876

Table 3: Wilcoxon signed rank test result based on 10-dimension test functions.

	R+	R-
SKFWH vs SKF	422	**43**

Table 4: Wilcoxon signed rank test result based on 50-dimension test functions.

	R+	R-
SKFWH vs SKF	352	**113**

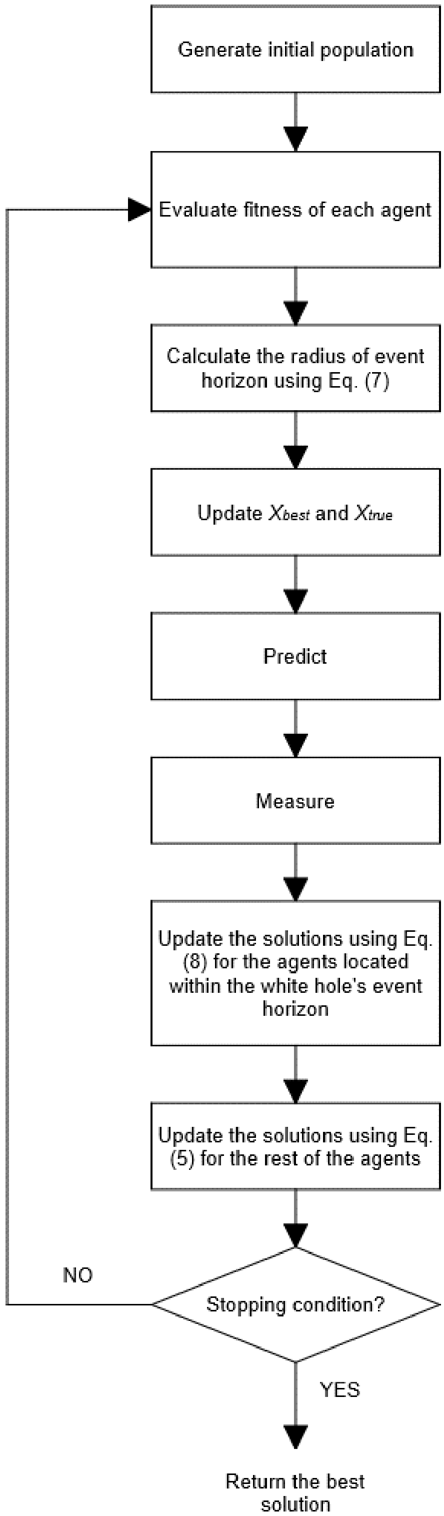

Fig. 3: The SKF algorithm with white hole operator (SKFWH).

Table 5: The mean fitness based on 10, 50, and 100 agents. The total number of function evaluation is 1,000,000.

No.	10 agents	50 agents	100 agents
1	6842461.074	8249749.934	4599371.793
2	7557.765436	67721025.25	2584405.723
3	7180.761822	20435.18084	15654.3802
4	558.8601389	542.2949562	525.7442982
5	520.0008579	520.0000267	520.0000447
6	634.3263996	626.2770105	622.5405876
7	700.0483049	700.2555538	703.775289
8	801.6259361	805.221172	804.4771155
9	1110.712509	1072.622085	1060.718543
10	1021.795305	1164.888077	1167.850431
11	6629.145251	6370.193368	6280.91523
12	1200.248523	1200.206515	1200.197155
13	1300.548525	1300.564763	1300.564131
14	1400.314432	1400.310443	1400.315442
15	1574.222179	1578.482811	1550.736579
16	1619.069307	1619.797243	1618.971832
17	1890246.778	911763.8217	815048.4382
18	3002.950783	23965767.71	7320683.517
19	1961.263909	1945.459122	1941.608824
20	5638.838995	36236.62629	31143.98421
21	1716825.937	1470818.982	1140601.748
22	3551.80744	3464.577495	3414.761688
23	2648.322643	2650.848828	2645.270911
24	2662.889529	2664.03135	2661.797998
25	2738.206645	2732.394866	2730.285585
26	2784.405028	2786.437922	2782.399055
27	4182.280784	3949.888038	3876.071383
28	8604.909235	7560.618167	6834.144597
29	4595.713531	57578.34953	8049.657217
30	19464.09273	27855.13969	19708.47701

Table 6: Wilcoxon signed rank test based on the result in Table 5.

	R+	R-
10 agents vs 50 agents	207	258
10 agents vs 100 agents	274	191
50 agents vs 100 agents	442	**23**

Table 7: The mean fitness based on 50-dimension test functions

No.	$P = 1$	$P = 10$	$P = 100$	$P = 10000$
1	4767397	4543595	4667601	4702013
2	1725833	5617675	12082776	1764059
3	17351	16283	18639	18937
4	537	521	529	529
5	520	520	520	520
6	636	638	632	632
7	700	700	700	700
8	804	804	803	804
9	1067	1056	1059	1061
10	1213	1179	1171	1218
11	6011	6063	6288	5938
12	1200	1200	1200	1200
13	1300	1300	1300	1300
14	1400	1400	1400	1400
15	1549	1548	1546	1551
16	1618	1619	1619	1619
17	921673	881715	792874	942630
18	7279155	6879170	7985422	3360283
19	1942	1946	1946	1949
20	31074	34361	31820	31710
21	1072313	1246738	1280575	1215168
22	3447	3392	3358	3348
23	2645	2645	2646	2645
24	2663	2661	2665	2662
25	2730	2730	2730	2730
26	2778	2778	2788	2784
27	3890	3858	3889	3892
28	6907	7199	7095	6920
29	12651	12599	5492	6212
30	19032	19734	19928	18915

Table 8: Wilcoxon signed rank test based on the result in Table 7.

	R+	R-
1 vs 10	275	190
1 vs 100	194	271
1 vs 1000	216	249
10 vs 100	178	287
10 vs 1000	237	228
100 vs 1000	262	203

Table 9: The mean fitness based on 10, 100, and 1000 agents. The number of iterations is 100 and the number of dimensions is 50.

No.	10 agents	100 agents	1000 agents
1	1338145210	327605271	116205335
2	79184268726	24854725947	8938780098
3	235022.9	101045.4	43799.9
4	17994.29	4197.986	1711.866
5	521.2865	521.1728	521.0734
6	667.432	658.1857	642.7808
7	1587.334	2781.969	725.332
8	1315.766	1161.581	1090.504
9	1526.552	1359.62	1267.708
10	12887.08	10302.09	8891.271
11	14446.95	12404.72	11200.69
12	1204.309	1202.841	1202.375
13	1305.891	1303.342	1300.934
14	1589.182	1461.033	1420.469
15	1403735	24170.85	2578.101
16	1623.134	1622.352	1621.448
17	225197269	35122256	7038724
18	6262617231	268449390	9439867
19	2652.459	2054.65	1994.275
20	373457.8	42918.45	14015.08
21	58530680	8650934	4298820
22	44469.24	3944.376	3346.909
23	3411.079	2813.781	2702.812
24	2813.254	2734.035	2708.263
25	2813.406	2757.566	2741.351
26	2847.602	2787.787	2754.411
27	4932.037	4404.915	4089.907
28	16155.92	11652.09	8520.319
29	907086143	96761146	7618629
30	11357918	1580825	339916.2

Table 10: Wilcoxon signed rank test based on the result in Table 9.

	R+	R-
10 vs 100	450	**15**
10 vs 1000	465	**0**
100 vs 1000	465	**0**

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