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An Improved Sine Cosine Algorithm for Solving Optimization Problems

M. H. Suid
Faculty of Electrical and Electronics Engineering
Universiti Malaysia Pahang
Pekan, Malaysia
mhelmi@ump.edu.my

M. A. Ahmad
Faculty of Electrical and Electronics Engineering
Universiti Malaysia Pahang
Pekan, Malaysia
mashraf@ump.edu.my

M. R. T. R. Ismail
Faculty of Electrical and Electronics Engineering
Universiti Malaysia Pahang
Pekan, Malaysia
rajamohd@ump.edu.my

M. R. Ghazali
Faculty of Electrical and Electronics Engineering
Universiti Malaysia Pahang
Pekan, Malaysia
riduwan@ump.edu.my

A. Irawan
Faculty of Electrical and Electronics Engineering
Universiti Malaysia Pahang
Pekan, Malaysia
addieirawan@ump.edu.my

M. Z. Tumari
Faculty of Engineering Technology
Universiti Teknikal Malaysia Melaka
Ayer Keroh, Melaka
mohdzaidi.tumari@utem.edu.my

***Abstract*— Due to its simplicity and less tedious parameter tuning over other multi-agent-based optimization algorithms, Sine Cosine Algorithm (SCA) has gotten lots of attention from numerous researchers for resolving optimization problem. However, the existing SCA tends to have low optimization precision and local minima trapping effect due to the constraint in its exploration and exploitation mechanism. To overcome this drawback, an extensive version of SCA named Improved Sine Cosine Algorithm (iSCA) has been proposed in this work. The main concept is to introduce a nonlinear control strategy to the existing SCA's exploration and exploitation process in order to synthesize the algorithm's strength. The efficiency of this suggested algorithm is assessed using 23 classical well-known benchmark functions and the results are then verified by a comparative study with several other algorithms namely Ant Lion Optimizer (ALO), Multi-verse Optimization (MVO), Spiral Dynamic Optimization Algorithm (SDA) and Sine Cosine Algorithm (SCA). Experimental results show that the iSCA is very competitive compared to the state-of-the-art meta-heuristic algorithms.**

Keywords*— Optimization, Meta-heuristic Algorithm, Physics-based optimization, Sine Cosine Algorithm (SCA), Improved Sine Cosine Algorithm (iSCA).

I. INTRODUCTION

Global optimization issues are continuously inevitable. As the intricacy of problems have actually been raising over the last couple of years, the requirement for brand-new optimization technique have come to be apparent than ever before. Of late, meta-heuristic optimization technique has become very popular day by day due to its simplicity, flexibility and the ability to avoid stagnation in local solution [1]. For example, some of the meta-heuristic optimization techniques such as Genetic Algorithm (GA) [2], Gravitational Search Algorithm (GSA) [3] and Particle Swarm Optimization (PSO) [4] are fairly recognized not only among the computer science researchers but also attracts other researchers from many diverse fields such as engineering, management and medical sciences [5].

In theory, optimization describes a series of actions in discovering the feasible ideal solutions for a particular problem from all the potential values for maximizing/minimizing its outcome. Generally, meta-heuristic optimization can be distinguished into two main classes, i.e. 1) single-agent-based and 2) multi-agent-based. In the former class, the search process starts with randomization of single solution then it will improve over the sequence of iterations. Meanwhile in the latter class, the objective searching process will start with a set of random initial solutions and this solution is enhanced over the sequence of iterations. The class of multi-agent-based can be grouped in three key categories depends on the inspiration of an algorithm i.e. evolution-based, physics-based, and swarm-based methods. One of the interesting branches of the multi-agent-based optimization is physics-based algorithms, which the concept was first introduced in 1996 [6]. Most of the algorithms in this domain typically simulate and replicate the physical rules in nature. The mechanism is almost similar to the evolutionary algorithms, but the search agents communicate and navigate throughout search space according to physical rules. Physics-based algorithms include many algorithms such Gravitational Local Search Algorithm (GLSA) [7], Black Hole (BH) [8], Big Bang Big Crunch (BBBC) [9], Curved Space Optimization (CSO) [10], Ray Optimization (RO) [11] and many others. This movement implemented for example using gravitational force, ray casting, electromagnetic force and weights.

Recently, there is an additional physics-based algorithm which is established by Mirjalili et al. in 2016 called Sine Cosine Algorithm (SCA) [12]. In this algorithm, the solutions were called for to update their positions relative to the most effective solution found thus far, as the destination point through sine-cosine mathematical functions. Conceptually, the SCA algorithm is simple to be implemented and has less parameter setting. So far, SCA has been successfully applied for solving feature selection problem [13], image binarization [14], shell and tube evaporator design problem [15], speed reducer problem [16] and many other engineering difficulties. However, the existing SCA has the disadvantage of low optimization precision and premature convergence problem.

Therefore, a new version of SCA named Improved Sine Cosine Algorithm (iSCA) is proposed in this study to better balance the exploration and exploitation ability of the original SCA algorithm. Nonlinear functions with diverse slopes are employed to tune the parameters of classical SCA algorithm for varying exploration and exploitation combinations over the sequence of iterations. The rest of this paper is arranged as follows. The basic of conventional SCA algorithm is briefly explained in Section 2. The proposed extensive version of SCA (i.e. iSCA) algorithm is presented in Section 3. Meanwhile, the evaluation of the proposed optimization technique together with several other existing meta-heuristics algorithms using 23 classical benchmark functions are discussed in detail in Section 4. Finally, the conclusion is given in Section 5.

II. Overview of Sine Cosine Algorithm (SCA)

SCA is multi-agent-based optimization algorithm which its update roles are established based on the mathematical trigonometric sine and cosine functions. Generally speaking, it is very simple from the mathematical and algorithmic viewpoints. Similar to other meta-heuristic optimization techniques, SCA starts the search process by creating set of solutions/search agents which are positioned randomly in the search space. Next off, these solutions are assessed via using the objective function. After that the algorithm keeps the better solution acquired thus far, signifies it as the location point and the solutions are updated to produce new solutions in accordance with the sine and cosine functions (see Eq. (1) and Eq. (2)). This optimization procedure will be recurring continuously until it finally halt when maximum number of iterations is achieved.

$$X_i^{t+1} = X_i^t + r_1 \bullet \sin(r_2) \bullet \left| r_3 P_i^t - X_i^t \right| \quad (1)$$

$$X_i^{t+1} = X_i^t + r_1 \bullet \cos(r_2) \bullet \left| r_3 P_i^t - X_i^t \right| \quad (2)$$

where X_i^t is the position of the current solution and P_i^t is position of the destination point in *i-th* dimension at *t-th* iterations, respectively. These two aforementioned equations are then could be composed and used as follows:

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \bullet \sin(r_2) \bullet \left| r_3 P_i^t - X_i^t \right|; & \text{if } r_4 < 0.5 \\ X_i^t + r_1 \bullet \cos(r_2) \bullet \left| r_3 P_i^t - X_i^t \right|; & \text{if } r_4 \geq 0.5 \end{cases} \quad (3)$$

where r_1, r_2, r_3, r_4 are random variables which act as SCA's key parameters and || indicates the absolute value. The parameter r_2 describes exactly how much the motion of solution approaching or leaving the destination should be and r_3 carries a random weight for the destination in order to stochastically emphasize; (when $r_3 > 1$) and deemphasize; (when $r_3 < 1$) the effect of destination in specifying the distance. Parameter r_4 is used to randomly switch between sine and cosine functions in Eq. (3), it is ranging between [0,1].

As the above equations show that the parameter r_1 is responsible for determine the area of the next solution, this area may be either to go around space between and (i.e. exploration phase) or inside them (i.e. exploitation phase). In order to balance the exploration and exploitation capabilities, the range of sine/cosine in Eqs. (1)-(3) is updated adaptively according to the following equation:

$$r_1 = a - t\frac{a}{T} \quad (4)$$

where t is the current iterations, T is the maximum number of iterations and a is a constant which will decrease the range of sine/cosine functions linearly from a to 0 (typically $a = 2$) over the sequence of iterations. Basically, when the ranges of sine and cosine functions remain in the range [1, 2] and [-2, -1], the SCA will be in the global space exploration mode. Otherwise, the SCA will exploit the local search space when the ranges are in the interval of [-1, 1].

III. Improved Sine Cosine Algorithm (iSCA)

The newly proposed version of SCA called Improved Sine Cosine Algorithm (iSCA) is discussed more specifics in this section. Briefly, the work in this research direction is focused on improving the performance of the original SCA algorithm via enhancing its updating mechanism in Eq. (4).

In its current version of the SCA algorithm, half of the iterations are dedicated to exploration phase ($r_1 \geq 1$) and also the further fifty percent are used for exploitation phase ($r_1 < 1$). Theoretically, exploration as well as exploitation are two contradictory cornerstones where promoting one outcomes will certainly be deteriorating the various other in returns. Mere exploration of the search area prevents an algorithm from discovering a precise estimation of the global optimum. In contrast, mere exploitation results in local optima stagnancy and once again, low quality of the approximated optimum. Appropriate selection of the control parameter can offer a much healthier balance between local exploitation and global exploration. There are various potentials to enhance the exploration and exploitation processes. Among it is by examining the mechanism of its control parameter r_1. In the existing SCA algorithm, the value of r_1 in Eq. (4) decreases linearly from 2 to 0. Considering that the search process of the SCA algorithm is nonlinear and also a little bit complicated, the linear control approach towards parameter r_1 cannot really reveal the real search process. Based on the consideration stated above, a nonlinear decreasing control strategy which based on exponential function is then adopted in the updated mechanism of classical SCA algorithm; rather than being a linearly decreasing. This newly proposed updating mechanism is described by Eq. (5) as follows:

$$\hat{r}_1 = a\left(1 - \left(\frac{t}{T}\right)^{\alpha}\right)^{\beta} \quad (5)$$

where t is the current iterations, T indicates the total number of iterations. Meanwhile, both α and β are the nonlinear modulation index of the proposed iSCA algorithm (i.e. constants with positive real number). By introducing this nonlinear decreasing function into the existing SCA's mechanism, the number of iterations used for exploration and exploitation can be more properly tuned.

Generally, at the commencement phase of the SCA algorithm, the population has a greater diversity. A greater population diversity means that the capability to explore the global space is stronger yet the objective of this phase is to speed up convergence. Therefore, the value of control parameter $\hat{r}_1$ in the proposed iSCA algorithm is set to a smaller value in which less than 2. On contrary at the local exploitation stage, the population should take cautious stance in order to improve the searching precision and avoiding easily local trapped phenomenon. The proposed nonlinear updating parameter $\hat{r}_1$ variations with iterations for different values of α and β are shown in Fig. 1 and Fig. 2, respectively. Finally, the steps of the iSCA are elucidated in Algorithm 1, where X_i is the*i-th* element of vector X and P_i is the *i-th* element of vector P.

Algorithm 1. Pseudo code of iSCA Algorithm

begin iSCA Algorithm Main
Randomly initialize X_i (i = 1, 2, ..., Dim) for each agents;
Set the max numbers of iteration T;
while $t < T$
for each agent X_i in the population **do**
Estimate X_i using the fitness function. **if** $f(X)$ better than $f(P)$
then
Set $P = X$;
end
end
Update $\hat{r}_1$ using Eq. (5).
Produce randomly new values for r_2 , r_3 and r_4 .
for each agent X_i in the population **do**
Update X_i using Eq. (3).
end
end
Return best solutions obtained so far as destination point P.
end

* the source code of Algorithm 1 can be downloaded from the following link: *http://bit.do/ISCA*

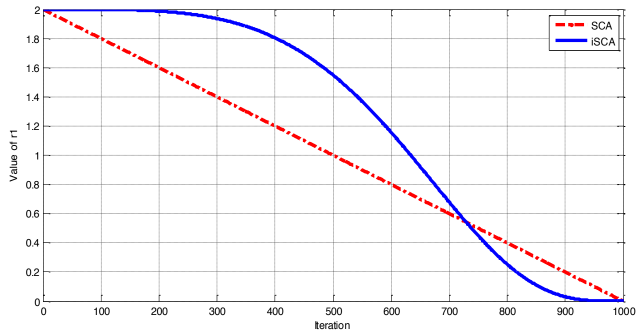

Fig. 1: Updating value of r_1 for SCA and $\hat{r}_1$ for iSCA (α =3.98, β =3.9).

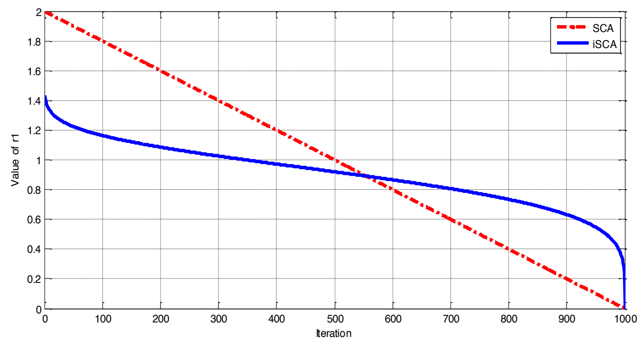

Fig. 2: Updating value of r_1 for SCA and $\hat{r}_1$ for iSCA (α =0.03, β =0.2).

IV. Experimental Results and Discussion

The proposed method is an interesting alternative to the classical version of SCA for global optimization. In order to investigate the effectiveness of iSCA in practice, a set of 23 different benchmark or test functions has been used in this experiment. Basically, these benchmark functions are categorized into three groups: unimodal benchmark function, multimodal benchmark function and fixed-dimension multimodal benchmark function. The unimodal functions (F_1-F_7) are suitable to be used for benchmarking the exploitation ability or the precision of the algorithm since they only have one global solution. Meanwhile, (F_8-F_{13}) are multimodal functions that are very useful to analyse the algorithm's exploration ability along with its capability to avoid poor local optima stagnancy as these multimodal functions have many local optima regions [17]. The function name, dimension, search range (i.e. the boundary of functions search space) and theoretical optimal value, F_{min} are shown in Tables I-III.

For verifying the results, the proposed iSCA algorithm (with its tuning parameters a =2, α =0.03 and β =0.2) is compared to Sine Cosine Algorithm (SCA) [12], Ant Lion Optimizer (ALO) [18], Multi-verse Optimization (MVO) [19] and Spiral Dynamic Optimization Algorithm (SDA) [20]. All these optimization algorithms were run 30 times on each benchmark functions using a total of 30 search agents and 1000 iterations. The experimental results (statistical average) are then reported in Tables IV-VI. The results of the implemented optimization algorithms will be interpreted objectively and subjectively as to judge the algorithms effectiveness in discovering feasible ideal solutions.

TABLE I. Unimodal Benchmark Functions

Function	Dim	Range	F_{min}
F_1 (Sphere)	30	[-100,100]	0
F_2 (Schwefel 2.22)	30	[-10,10]	0
F_3 (Schwefel 1.2)	30	[-100,100]	0
F_4 (Schwefel 2.21)	30	[-100,100]	0
F_5 (Resenbrock)	30	[-30,30]	0
F_6 (Step)	30	[-100,100]	0
F_7 (Quartic)	30	[-1.28,1.28]	0

TABLE II. Multimodal Benchmark Functions

Function	Dim	Range	F_{min}
F_8 (Schwefel)	30	[-500,500]	-418.9829×Dim
F_9 (Rastrigin)	30	[-5.12,5.12]	0
F_{10} (Ackley)	30	[-32,32]	0
F_{11} (Griewank)	30	[-600,600]	0
F_{12} (Penalized)	30	[-50,50]	0
F_{13} (Penalized 2)	30	[-50,50]	0

TABLE III. Fixed-Dimension Multimodal Benchmark Functions

Function	Dim	Range	F_{min}
F_{14} (Foxholes)	2	[-65.536,65.536]	0.998004
F_{15} (Kowalik)	4	[-5,5]	0.00030
F_{16} (Six-hump Camel Back)	2	[-5,5]	-1.0316
F_{17} (Branin)	2	[-5,5]	0.398
F_{18} (Goldstein-Price)	2	[-2,2]	3
F_{19} (Hartman 3)	3	[1,3]	-3.86
F_{20} (Hartman 6)	6	[0,1]	-3.32
F_{21} (Shekel 5)	4	[0,10]	-10.1532
F_{22} (Shekel 7)	4	[0,10]	-10.4028
F_{23} (Shekel 10)	4	[0,10]	-10.5363

As can be seen in unimodal test function (see Table IV), the iSCA algorithm manage to provide the best results in five out of seven readings. The iSCA also gives very competitive results compared to MVO and SDA on functions F_3 and F_6 respectively. These results shows that the proposed iSCA algorithm has a great strength in searching precision of unimodal problems. For the meantime, from the experimental results of the multimodal functions in Table V it is clearly seen that the iSCA algorithm highly outperforms other algorithm on F_9, F_{10} and F_{12}. Next, even though SCA provides the slightly better reading in function F8, but the value is nearly the same as those produced by iSCA algorithm. The same trend can also be seen in function F_{13} where iSCA manages to produce slightly better results than ALO. For that reason, it can be claimed here that the iSCA algorithm not only has a high exploration capability but it also strongly prove that this proposed algorithm also able to get away from local optima stagnation problem. The rest of the results which belong to the fixed-dimension multimodal benchmark function can be observed in functions F_{14}-F_{23} (see Table VI). The resultant readings are consistent with various other test features, wherein the suggested iSCA algorithm displays very competitive results as contrasted to other optimization methods.

TABLE IV. MINIMIZATION RESULTS OF UNIMODAL BENCHMARK FUNCTIONS

Function	ALO	MVO	SDA	SCA	iSCA
F_1	1.04E-05	2.81E-01	5.45E-05	3.55E-02	***1.05E-10***
F_2	5.08E+01	4.22E-01	5.08E+05	2.90E-05	***5.62E-13***
F_3	1.12E+03	4.41E+01	6.07E+03	4.43E+03	***7.69E+02***
F_4	1.25E+01	9.99E-01	9.35E+00	1.82E+01	***6.06E+00***
F_5	121.6281	249.8207	4242.5016	322.8683	***28.0928***
F_6	***0.0000***	0.3243	0.0001	4.7204	4.2411
F_7	0.0983	0.0206	0.1860	0.0364	*0.0148*

TABLE V. MINIMIZATION RESULTS OF MULTIMODAL BENCHMARK FUNCTIONS

Function	ALO	MVO	SDA	SCA	iSCA
F_8	-5684.951	-8087.144	-5914.811	***-3954.447***	-3610.345
F_9	80.5915	117.4333	191.6287	16.7573	***3.2078***
F_{10}	2.16E+00	1.15E+00	1.34E+01	1.37E+01	***2.23E-04***
F_{11}	***0.0123***	0.5775	0.0154	0.3017	0.0202
F_{12}	10.6160	1.5110	2.6984	643.9264	***0.5593***
F_{13}	3.9263	0.0750	***0.0524***	381.8873	2.3400

TABLE VI. MINIMIZATION RESULTS OF FIXED-DIMENSION MULTIMODAL BENCHMARK FUNCTIONS

Function	ALO	MVO	SDA	SCA	iSCA
F_{14}	1.9214	***0.9980***	1.0641	1.4611	3.0276
F_{15}	0.0035	0.0046	0.0411	0.0009	***0.0007***
F_{16}	-1.032	-1.032	-1.032	-1.032	***-1.032***
F_{17}	0.3979	0.3979	0.3979	0.3989	0.3986
F_{18}	3.0000	8.4000	6.0037	3.0000	***3.0000***
F_{19}	-0.3005	-0.3005	-0.1061	-0.3005	***-0.3005***
F_{20}	***-3.2784***	-3.2464	-3.1508	-3.0231	-2.9105
F_{21}	-6.7031	***-7.8793***	-5.4820	-3.0791	-4.0579
F_{22}	-7.3391	***-9.6195***	-7.3420	-3.8712	-4.5976
F_{23}	-6.8456	***-8.8413***	-6.1386	-4.3168	-4.4382

In addition to the analysis which has been discussed above, this study has further evaluated the minimization improvement performance in percentage for all 23 benchmark functions tested and the results are displayed in Table VII. It could be clearly observed that the proposed iSCA optimization technique outperforms the classical version of SCA in the majority of the tested benchmark functions. Except for the benchmark functions F_8, F_{14} and F_{20} where the SCA algorithm has a slightly better readings and another three functions (i.e. F_8, F_{14}, and F_{20}) in which both algorithms having the same performance results, other functions have shown that iSCA algorithms is able to yield much superior scores with ≈100% improvement against its competitor especially for functions F_1, F_2, F_{10}, F_{12} and F_{13}. Thus, it is possible to conclude that the iSCA proved efficiency and adeptness in finding the global optimal values of optimization problems.

TABLE VII. PERFORMANCE IMPROVEMENT OF MINIMIZATION RESULTS

Function	SCA	iSCA	Improvement (%)
F_1	3.55E-02	***7.23E-10***	(+) 100.00
F_2	2.90E-05	***5.62E-13***	(+) 100.00
F_3	4.43E+03	***7.69E+02***	(+) 82.64
F_4	1.82E+01	***6.06E+00***	(+) 66.70
F_5	322.8683	***28.0928***	(+) 91.30
F_6	4.7204	***4.2411***	(+) 10.15
F_7	0.0364	***0.0148***	(+) 59.34
F_8	***-3954.447***	-3610.345	(*) 8.70
F_9	16.7573	***3.2078***	(+) 80.86
F_{10}	1.37E+01	***2.23E-04***	(+) 100.00
F_{11}	0.3017	***0.0202***	(+) 93.30
F_{12}	643.9264	***0.5593***	(+) 99.91
F_{13}	381.8873	***2.3400***	(+) 99.39
F_{14}	***1.4611***	3.0276	(*) 51.74
F_{15}	0.0009	***0.0007***	(+) 22.22
F_{16}	-1.032	-1.032	0.00
F_{17}	0.3989	***0.3986***	(+) 0.08
F_{18}	3.0000	3.0000	0.00
F_{19}	-0.3005	-0.3005	0.00
F_{20}	***-3.0231***	-2.9105	(*) 3.72
F_{21}	-3.0791	***-4.0579***	(+) 31.79
F_{22}	-3.8712	***-4.5976***	(+) 18.76
F_{23}	-4.3168	***-4.4382***	(+) 2.81
* Indicates SCA performance is better. + Indicates iSCA performance is better.			

V. CONCLUSION

As an innovative meta-heuristic optimization, the Sine Cosine Algorithm (SCA) has actually so much been effectively applied in numerous of areas. Here in this research, a new enhanced version of SCA algorithm (denoted as iSCA) is introduced for dealing with continual big scales optimization problems. The main idea is to properly balance the convergence speed and convergence precision by adopting the nonlinear decreasing control strategy into the existing SCA's updating mechanism. 23 typical benchmark functions are used to verify the performance of the proposed iSCA algorithm compared to standard SCA, ALO, MVO and SDA. The investigational results show that the suggested algorithm iSCA could deliver extremely competitive end results compared to the various other existing advanced algorithms in the majority of function minimization cases. These preliminary findings show that the proposed algorithm has an ability to become an effective tool for solving real world optimization problems.

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