A Hybrid Sine Cosine Optimization Algorithm for Solving Global Optimization Problems

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Abstract

- SCA is a new efficient population-based optimization algorithm proposed in 2016.
- SCA still may face the problem of getting trapped in local optima regarding insufficient diversity of the agents and their unbalanced exploration/exploitation trends in some cases.
- To avoid these issues, SCA is integrated with a local search techinque to solve the global optimization problems.

Problem formulation

A nonlinear programming problem is stated as follows:

$$\text{Min}_{\Omega}\ f(\mathbf{x}) = f(x_1, x_2, \ldots, x_n)$$

$$\text{Subject to: } \mathbf{x} \in \Omega,$$

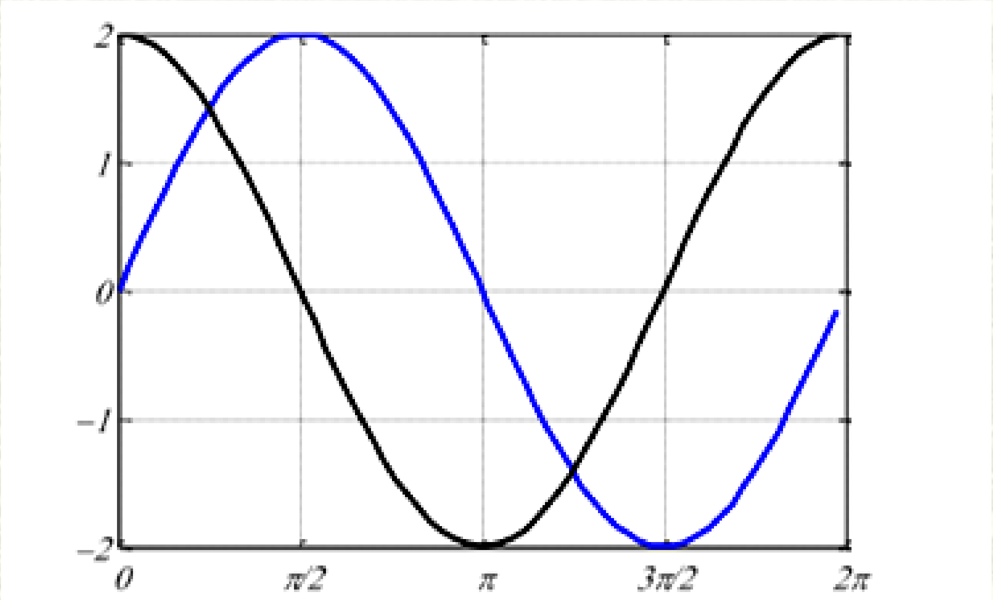
$$\Omega = \left\{ \begin{array}{l} \mathbf{x} \mid g_j(\mathbf{x}) \le 0,\ j = 1,\ldots,q,\ h_j(\mathbf{x}) = 0,\ j = q+1,\ldots.,m, \\ LB_i \le x_i \le UB_i,\ i = 1,\ldots.,n \end{array} \right\}$$

Global minimum : For the function $f : \Omega \subseteq \mathbb{R}^n \to R,\ \Omega \ne \phi,$

the value $f^* \triangleq f(\mathbf{x}^*)$ **is called a global minimum if and only if** $\forall \mathbf{x} \in \Omega:\ f(\mathbf{x}^*) \le f(\mathbf{x})$

A Sine Cosine Algorithm (SCA)

SCA is population-based optimization algorithm that is established based on the mathematical sine and cosine functions



Sine and cosine with range of [-2,2]

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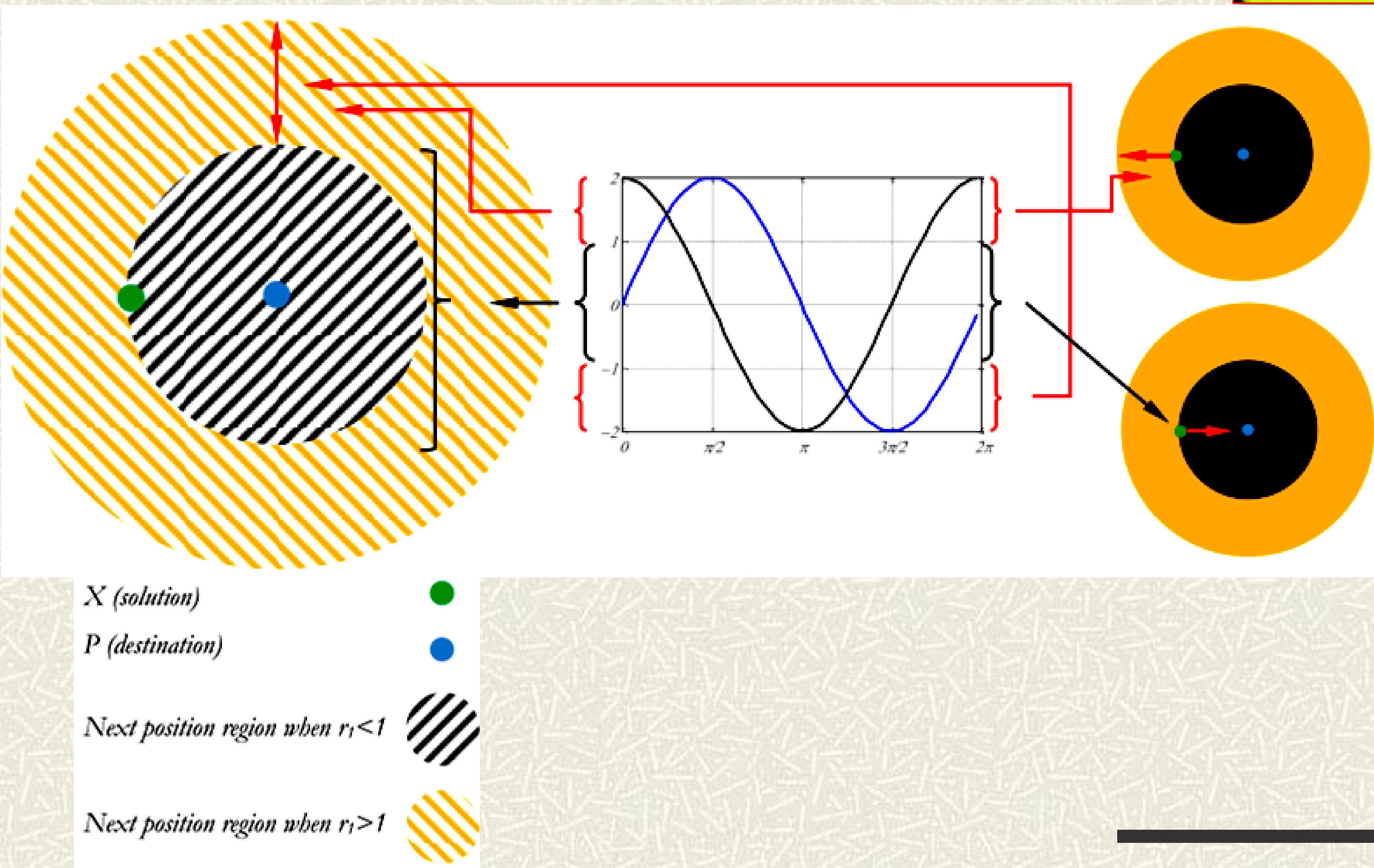


The main stages of SCA

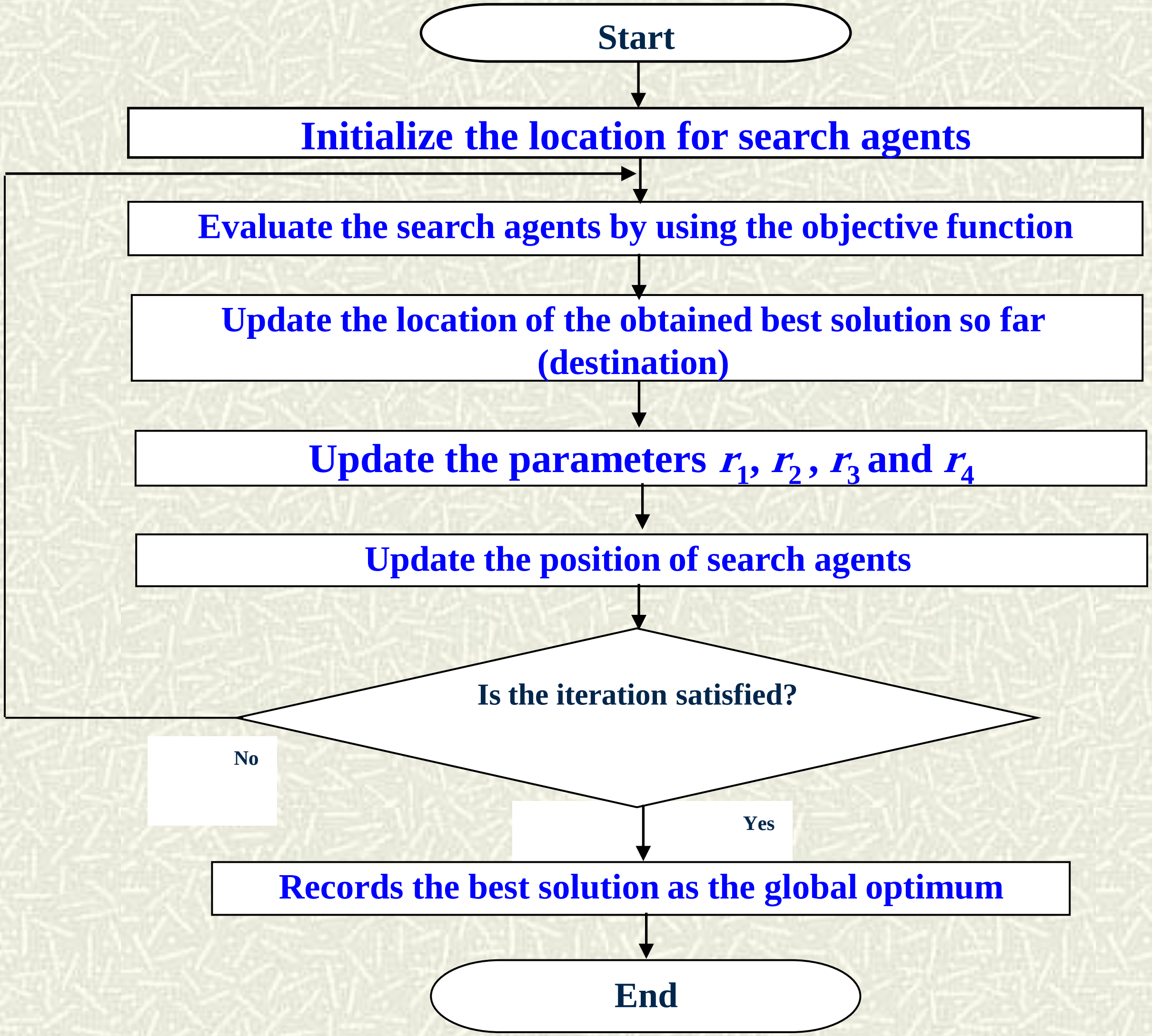
- **Evaluation which is accomplished using the objective function**

- **Solutions update**

$$\mathbf{x}_{i,t+1} = \begin{cases} \mathbf{x}_{i,t} + r_1 \times \sin(r_2) \times | r_3 P_{i,t} - \mathbf{x}_{i,t} | & r_4 < 0.5 \\ \mathbf{x}_{i,t} + r_1 \times \cos(r_2) \times | r_3 P_{i,t} - \mathbf{x}_{i,t} | & r_4 \geq 0.5 \end{cases}$$

$$i = 1, 2, ..., PS$$

$$r_1 = a - \frac{a \times t}{T}$$



Start
Initialize the location for search agents
Evaluate the search agents by using the objective function
Update the location of the obtained best solution so far (destination)
Update the parameters r_1, r_2 , r_3 and r_4
Update the position of search agents
Is the iteration satisfied?
No
Yes
Records the best solution as the global optimum
End

r_1 dictates the next position regions.

r_2 defines how far the movement should be towards or outwards the destination.

r_3 gives random weights for destination in order to stochastically emphasize ($r_3 > 1$) or deemphasize ($r_3 < 1$) the effect of desalination in defining the distance.

Finally, the parameter r_4 equally switches between the sine and cosine components .

The advantages and disadvantages of SCA

- It is very simple from the mathematical and algorithmic standpoints
- it provides in many instances highly accurate results

- this algorithm might not be able to outperform other algorithms on specific set of problems.
- Existence of four random parameters

The Local Search phase

The search procedure looks for the best solution "near" another solution by repeatedly making small changes to a starting solution until no further improved solutions can be found.

$$x_{+} = x_{t} \pm \Delta(t).e_{i}\ , \quad (i = 1, 2, .., n)$$

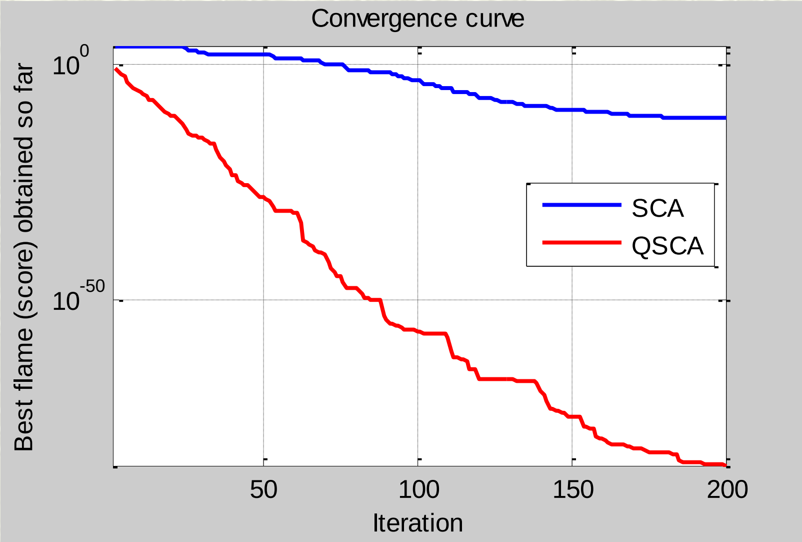
$$\Delta(t) = R(1 - r^{(1-t/T)})$$

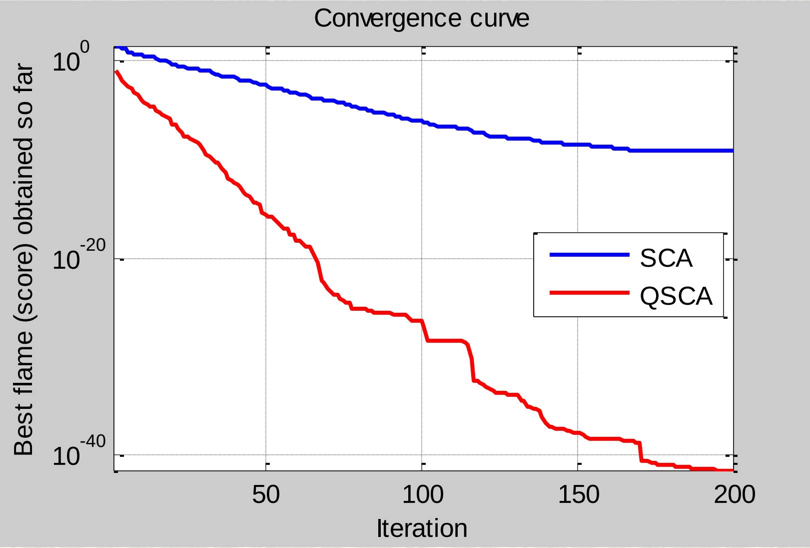
Results and discussion

In section some test functions are collected and reported in Table 1

Function	Dim	Range
$f_1(x) = \sum_{i=1}^{n} x_i^2$	20	[-100,100]
$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	20	[-10,10]
$f_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j \right)^2$	20	[-100,100]
$f_4(x) = \max_i \{ \lvert x_i \rvert, 1 \le i \le n \}$	20	[-100,100]
$f_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	20	[-30,30]
$f_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	20	[-100,100]
$f_7(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1)$	20	[-1.28,1.28]

	F1		F2	
Algorithm	**SCA**	**Modified SCA**	**SCA**	**Modified SCA**
Best	٦,٦٦٤٩٣٢E-014	2.078186E-085	1.7105E-011	7.18184E-044
Worst	٨,٤٥٧٣٧٤E-009	٩,٤٢٥٧٥٧E-071	١,٠٢٢٠٩E-009	7.05777E-025
Mean	٩,١٤٣٣٥١E-010	٣,١٤٢١٥٧E-071	٣,١٨٦٣٦E-010	7.49224E-026
Std. dev.	٢,١٣٨٠٩٤١٥E-009	٥,٤٤١٧٥٧E-071	٢,٤٠٥٩١٠E-010	2.21859E-025





F1

F2

Pareto front of the best compromise solutions

Conclusion

The obtained result shows that the SCA based local serach is superior to the SCA. Additionally, it can escape the local minima and converge to the global minima efficiently.

For future works, it is possible to extent it to solve more complex problems.