A Novel Learning Multi-Swarm Particle Swarm Optimization

Bożena Borowska[1]

[1]*Lodz University of Technology*
Institute of Information Technology
Politechniki 8, 93-590 Łódź, Poland
bozena.borowska@p.lodz.pl

DOI:10.34658/9788366741928.53

Abstract. *Particle swarm optimization (PSO) is one of the metaheuristic optimization methods. Because of its many advantages, it is often used to solve real-world engineering problems. However, in case of complex, multi-dimensional tasks, PSO faces some problems related to premature convergence and stagnation in local optima. To eliminate this inconveniences, in this paper, a new learning multi-swarm particle swarm optimization method (LMPSO) with local search operator has been proposed. The presented approach was tested on a set of nonlinear functions and a CEC2015 test suite. The obtained results were compared with other optimization methods.*

Keywords: *learning particle swarm optimization, learning strategy, multi-swarm, particle swarm optimization, pso, optimization, swarm intelligence*

1. Introduction

Particle swarm optimization (PSO) is one of the nature-inspired metaheuristic methods used in real-world optimization problems. It was proposed by Kennedy and Eberhart [1] as an alternative to the genetic algorithm (GA). It is appreciated by scientists for its simplicity, robustness and search capability and is successfully applied in many different areas such as image segmentation [2, 3], feature selection [4, 5, 6], and many others. However, in case of complex, multi-dimensional tasks, PSO experiences some problems related to premature convergence and stagnation in local optimal solutions. To avoid this difficulties, in this paper, a new learning multi-swarm PSO method (LMPSO) with local Cauchy search operator has been proposed. LMPSO is a two-phase method. In the first phase the sub-swarms of the LMPSO method operate independently. In each sub-swarm, the particles learn from their neighbors. In the second phase the best particles of a sub-swarm can learn from the best particles of other sub-swarms. To more deeply search local area Cauchy operator is used. The presented approach was tested on a set of nonlinear functions and a CEC2015 test suite. The obtained results were compared with other optimization methods.

2. Standard PSO

Particle swarm optimization (PSO) is one of the nature-inspired methods used in optimization. It is based on a population called a swarm [7]. Swarm individuals are called particles. Each particle is described by a position vector $X_i=(x_{i1}, x_{i2}, \ldots, x_{iD})$ and a velocity vector $V_i=(v_{i1}, v_{i2}, \ldots, v_{iD})$. The velocity vector determines the speed and direction of particle motion. Each particle location represents one of the possible potential solutions to the problem under study. The goodness of the particle is evaluated by the fitness function. In the first iteration, the positions of the particles are randomly generated. Then they move in the search space and remember their best position (pbest) and the best position found in the entire swarm (gbest). In each iteration velocity of the particles is changing based on the equation 1:

$$V_i(t+1) = \omega V_i(t) + c_1 r_1(pbest_i - X_i(t)) + c_2 r_2(gbest - X_i(t)) \tag{1}$$

The position of the particles is updated according to the formula 2:

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{2}$$

where ω is the inertia weight, $pbest_i$ means the best i particle position, $gbest$ is the best position in a swarm, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are numbers generated from the uniform distribution on interval (0, 1).

3. Proposed Learning Strategy

The proposed LMPSO (learning multi-swarm particle swarm optimization) is a two-phase method based on particle swarm optimization, multi-swarm and learning concept. In the first phase the entire population of N particles is randomly divided into several sub-swarms. Each particle has a different position and velocity, and different searching abilities. During the search space all sub-swarms work independently. In each sub-swarm the particles move in the search space according to their velocity vectors and remember their best found position (*pbest*). The best position discovered in the entire sub-swarm is recorded as *sbest*. Half of the randomly selected particles of the sub-swarm update their position by learning from the average of the personal best positions ($\overline{pbest}$) found by all particles of the sub-swarm according to the formula 3 and 4:

$$V_i(t+1) = \omega V_i(t) + c_1 r_1(pbest_i - X_i(t)) + c_2 r_2(\overline{pbest} - X_i(t)) \tag{3}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{4}$$

where $pbest_i$ is the best position of the i particle, $\overline{pbest}$ is the average of the best personal positions found so far by the particles in sub-swarm.
The other half of the sub-swarm particles update their position by learning from

the best particle in the entire sub-swarm (*sbest*). The update proceeds according to the equations 5 and 4:

$$V_{\mathrm{i}}(t+1) = \omega V_{\mathrm{i}}(t) + c_1 r_1 (pbest_{\mathrm{i}} - X_{\mathrm{i}}(t)) + c_2 r_2 (sbest - X_{\mathrm{i}}(t)) \quad (5)$$

In the second phase, a temporary set E of the best particles (*sbest*) of each sub-swarm is created. Then the best particle from them is selected, and the other particles learn from it. In this way sub-swarms can share knowledge and learn from other sub-swarms. This means that good information found by one of the sub-swarms is not lost but can be used by other sub-swarms. Moreover, the sub-swarm that is trapped into local optimum can jump out of it by learning from the best particles of other sub-swarm. In addition, to deeply search vicinity area the local search Cauchy operator is used. The proposed strategy helps maintain population diversity and better search the space of possible solution.

4. Results

The tests of the proposed LMPSO method were performed on a set of classical benchmark problems and on the CEC 2015 functions [8]. The results of the tests were compared with performance of FIPS (fully informed particle swarm optimization) [9], MSPSO (pso with multiple subpopulations) [10] and PSO (standard particle swarm optimization).
For all tested algorithms, the population consist of 40 particles. The maximum number of iterations is 8000. The dimension of the search space was D=30. Inertia weight ω=0.9 to 0.4, sub-swarm's number s=4. For each problem, the algorithms were run 32 times independently. The exemplary research results for 5 functions from the CEC2015 set [8] are presented in Table1.

The results of the test indicate that the proposed LMPSO algorithm achieves superior performance over the other methods. Only in case of f3 function all algorithms reached similar average value but the mean value found by LMPSO was a bit better. However, it should be noted that LMPSO was slower than SPSO and FIPS but its results were more accurate. In case of f1, f2 and f6 function, the worst results were achieved by MSPSO. The MSPSO agorithm worked slower and performed worse in local optima. The FIPS algorithm generally performed better than the MSPSO method, but worse than LMPSO.
The proposed sub-swarm topology of LMPSO helps maintain diversity of the particles and improve exploration capacity. The learning strategy prevents the loss of valuable information found by swarms and improves effectiveness of the method. Cauchy operator increases exploitation ability and prevents stagnation in local optimum.

Table 1. The comparison test results

Function	Criteria	SPSO	MSPSO	FIPS	LMPSO
F1	Best	2.25E+04	4.19E+06	2.49E+06	1.56E+03
	Worst	2.11E+07	1.98E+07	1.26E+07	6.17E+05
	Mean	6.53E+06	1.21E+07	5.71E+06	8.98E+04
F2	Best	6.51E-08	3.05E+06	2.26E+01	1.83E-12
	Worst	1.59E-01	3.26E+07	1.20E+04	1.77E-08
	Mean	7.16E-03	1.38E+07	4.13E+03	1.31E-09
F3	Best	20.48E+00	20.67E+00	20.97E+00	20.50E+00
	Worst	21.90E+00	21.03E+00	21.18E+00	21.04E+00
	Mean	20.97E+00	20.98E+00	21.06E+00	20.78E+00
F4	Best	48.37E+00	51.44E+00	73.14E+00	41.20E+00
	Worst	112.03E+00	113.08E+00	151.13E+00	109.63E+00
	Mean	65.47E+00	88.65E+00	114.98E+00	56.24E+00
F6	Best	9.81E+04	1.12E+05	1.10E+05	3.25E+04
	Worst	1.52E+06	3.77E+06	1.14E+06	1.08E+05
	Mean	4.8953E+05	8.79E+05	4.32E+05	6.07E+04

5. Conclusions

In this study, a new two-phase multi-swarm particle swarm optimization (LMPSO) based on learning strategy and Cauchy search operator has been proposed. During the first phase sub-swarms works independently. The particles of the sub-swarm can move according the knowledge about their personal best position (pbest) and the mean best value of all particles in the sub-swarm or towards the best particle in the entire sub-swarm (sbest). In the second phase information is exchanges between sub-swarms. The effectiveness of LMPSO was tested on a set of nonlinear benchmark functions and a CEC2015 test functions.

References

[1] Kennedy J., Eberhart R.C., *Particle swarm optimization*, [In:] *Proceedings of the IEEE International Conference on Neural Networks*, Perth, Australia, 1995, pp. 1942–1948.

[2] Chander A., Chatterjee A., Siarry P., *A new social and momentum component adaptive pso algorithm for image segmentation*, *Expert Systems With Applications*, 2011, vol. 38, no 5, pp. 4998–5004, ISSN 0957-4174, doi: 10.1016/j.eswa.2010.09.151.

[3] Suresh S., Lal S., *Multilevel thresholding based on chaotic darwinian particle swarm optimization for segmentation of satellite images*, *Applied Soft Computing*, 2017, vol. 55, pp. 503–522, ISSN 1568-4946, doi: 10.1016/j.asoc.2017.02.005.

[4] Shafipour M., Rashno A., Fadaei S., *Particle distance rank feature selection by particle swarm optimization*, *Expert Systems with Applications*, 2021, vol. 185, p. 115620, ISSN 0957-4174, doi: 10.1016/j.eswa.2021.115620.

[5] Li A.D., Xue B., Zhang M., *Improved binary particle swarm optimization for feature selection with new initialization and search space reduction strategies*, *Applied Soft Computing*, 2021, vol. 106, p. 107302, ISSN 1568-4946, doi: 10.1016/j.asoc.2021.107302.

[6] Song X.F., Zhang Y., wei Gong D., yan Sun X., *Feature selection using barebones particle swarm optimization with mutual information*, *Pattern Recognition*, 2021, vol. 112, p. 107804, ISSN 0031-3203, doi: 10.1016/j.patcog.2020.107804.

[7] Kennedy J., Eberhart R.C., Shi Y., *Swarm Intelligence*, Morgan Kaufmann Publishers: San Francisco, CA, USA, 2001.

[8] Liang J., Qu B., Suganthan P., *Problem definitions and evaluation criteria for the cec 2015 competition on learning-based real-parameter single objective optimization*, Tech. rep., Nanyang Technological University (Singapore) and Zhengzhou University (China), 2014.

[9] Chang W.D., *A modified particle swarm optimization with multiple subpopulations for multimodal function optimization problems*, *Applied Soft Computing*, 2015, vol. 33, pp. 170–182.

[10] Mendes R., Kennedy J., Neves J., *The fully informed particle swarm: simpler, maybe better*, *IEEE Trans. Evol. Comput.*, 2004, vol. 8, pp. 204–210, doi: 10.1109/TEVC.2004.826074.