AIP Conference Proceedings

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Citation: AIP Conference Proceedings **1648**, 550022 (2015); doi: 10.1063/1.4912777

View online: http://dx.doi.org/10.1063/1.4912777

View Table of Contents: http://scitation.aip.org/content/aip/proceeding/aipcp/1648?ver=pdfcov

Published by the AIP Publishing

PSO Algorithm Enhanced with Lozi Chaotic Map - Tuning Experiment

Michal Pluhacek, Roman Senkerik and Ivan Zelinka

Tomas Bata University in Zlín, Faculty of Applied Informatics
Department of Informatics and Artificial Intelligence
nám. T.G. Masaryka 5555, 760 01 Zlín, Czech Republic

Abstract. In this paper it is investigated the effect of tuning of control parameters of the Lozi Chaotic Map employed as a chaotic pseudo-random number generator for the particle swarm optimization algorithm. Three different benchmark functions are selected from the IEEE CEC 2013 competition benchmark set. The Lozi map is extensively tuned and the performance of PSO is evaluated.

Keywords: PSO, Particle Swarm Optimization, Chaos, Lozi Map

INTRODUCTION

The Particle Swarm Optimization algorithm (PSO) [1 - 4] is one of the most widely used Evolutionary Computation Techniques (ECT's). In past years it was proposed that the implementation of chaotic sequences as chaotic pseudo-random number generators (CPRNG's) could significantly improve the performance of ECT's such as PSO on different optimization tasks [5 -10]. In this research it is examined the effect of different control parameters setting of Lozi chaotic map on the CPRNG and subsequently on the performance of chaos enhanced PSO algorithm.

PARTICLE SWARM OPTIMIZATION ALGORITHM

A brief description of PSO algorithm follows in this section. The PSO algorithm is inspired in the natural swarm behavior of birds and fish. It was introduced by Eberhart and Kennedy in 1995 [1]. Each particle in the population represents a candidate solution for the optimization problem that is defined by the cost function (CF). In each iteration of the algorithm, a new location (combination of CF parameters) for the particle is calculated based on its previous location and velocity vector (velocity vector contains particle velocity for each dimension of the problem). Within this research the PSO algorithm with global topology (GPSO) [6] was utilized. The chaotic PRNG is used in the main GPSO formula (1), which determines a new "velocity", thus directly affects the position of each particle in the next iteration.

$$v_{ij}^{t+1} = w \cdot v_{ij}^{t} + c_1 \cdot Rand \cdot (pBest_{ij} - x_{ij}^{t}) + c_2 \cdot Rand \cdot (gBest_j - x_{ij}^{t}) \tag{1}$$

Where:
v_i^{t+1} - New velocity of the *ith* particle in iteration t+1.
w – Inertia weight value.
v_i^{t} - Current velocity of the *ith* particle in iteration t.
c_1, c_2 - Priority factors
$pBest_i$ – Local (personal) best solution found by the *ith* particle.
gBest - Best solution found in a population.
x_{ij}^{t} - Current position of the *ith* particle (component j of dimension D) in iteration t.
Rand – Pseudo random number, interval (0, 1). CPRNG is applied only here.

The maximum velocity was limited to 0.2 times the range as it is usual. The new position of each particle is then given by (2), where x_i^{t+1} is the new particle position:

$$x_i^{t+1} = x_i^{t} + v_i^{t+1} \tag{2}$$

Finally the linear decreasing inertia weight [3, 4] is used in the typically referred GPSO design that was used in this study. The dynamic inertia weight is meant to slow the particles over time thus to improve the local search capability in the later phase of the optimization. The inertia weight has two control parameters wstart and wend. A

Proceedings of the International Conference on Numerical Analysis and Applied Mathematics 2014 (ICNAAM-2014)
AIP Conf. Proc. 1648, 550022-1–550022-4; doi: 10.1063/1.4912777

new w for each iteration is given by (3), where t stands for current iteration number and n stands for the total number of iterations. The values used in this study were wstart = 0.9 and wend = 0.4.

$$w = w_{start} - \frac{\left(\left(w_{start} - w_{end}\right) \cdot t\right)}{n} \tag{3}$$

LOZI CHAOTIC MAP

The Lozi map is a simple discrete two-dimensional chaotic map. The map equations are given in (4). The typical parameter values are: a = 1.7 and b = 0.5 with the respect to [11]. For these values, the system exhibits typical chaotic behavior and with this parameter setting it is used in the most research papers and other literature sources. This setting was also used in the previous research [8 - 10]. The x, y plot of Lozi map with the aforementioned typical setting is depicted in Fig. 1 (left), whereas the Fig. 1 (right) shows the distribution of CPRNG based on the Lozi map.

$$\begin{aligned} X_{n+1} &= 1 - a\left|X_n\right| + bY_n \\ Y_{n+1} &= X_n \end{aligned} \tag{4}$$

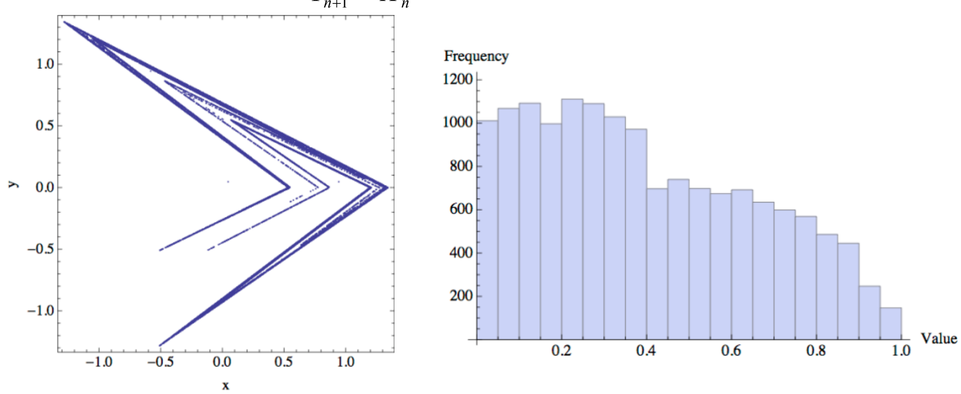

FIGURE 1. (left) x,y plot of the Lozi map; (right) CPRNG based on Lozi map – distribution histogram transferred into the range ⟨0, 1⟩ (15000 samples)

EXPERIMENT

Three different benchmark functions from the IEEE CEC`13 benchmark suite [12] were selected for the tuning experiments. The controlling parameters of the Lozi map were set as follows:

a: 1.3 - 1.7; step 0.05;

b: 0.1 - 0.6; step 0.05;

The Benchmark functions were evaluated for dim = 10; Pop. Size = 40; N. of iterations = 2500; According to [12] demands.

The PSO algorithm with adequately set CPRNG was run 100 times and mean results obtained for each function and Lozi map setting are presented in following tables. Table 1 – *f(2)*, Table 2 – *f(15)*, Table 3 – *f(28)*. The best obtained result for each function and corresponding control parameters are given in bold numbers. Subsequently the best performing combination of controlling parameters (a = 1.5 and b = 0.45) was investigated. The corresponding X,Y Plot and distribution of CPRNG is depicted in Fig. 2.

TABLE 1. Mean results comparison *f(2)*

a/b	0.1	0.15	0.2	0.25	0.3	**0.35**	0.4	0.45	0.5	0.55	0.6
1.3	180495	196970	166912	303321	844680	1405847	1490741	1177964	1281959	2005724	1865552
1.35	176931	115366	177566	145114	265418	722262	1421805	991068	1579318	1514804	1435695
1.4	127547	196461	145824	135722	123058	246978	690060	1120579	1664783	1561009	1623879
1.45	223858	198436	180462	219172	114462	**64981**	111100	782293	1767251	975486	1477080
1.5	387248	276620	328448	294575	290173	243915	147894	111241	778024	1050755	1281224
1.55	349128	238953	281811	252985	280306	147149	184247	277184	68986	1440386	1395371
1.6	288225	227259	257030	220875	260656	180732	244755	230776	264059	265551	1242494
1.65	286283	289920	253357	250453	173625	229633	156905	243705	210118	257486	510701
1.7	201308	217609	275955	335659	249680	263803	118640	210233	204447	176178	212454

TABLE 2. Mean results comparison *f(15)*

a/b	0.1	0.15	0.2	0.25	0.3	0.35	0.4	**0.45**	0.5	0.55	0.6
1.3	911	830	704	1344	1638	1569	1383	1389	1467	1356	1402
1.35	851	820	716	665	1057	1497	1383	1437	1481	1391	1285
1.4	753	703	689	676	655	838	1397	1416	1424	1229	1325
1.45	658	715	724	713	547	617	593	1214	1373	1276	1270
1.5	703	760	757	731	671	749	701	**534**	1203	1171	1217
1.55	725	732	699	752	702	713	750	762	625	1118	1204
1.6	679	826	737	701	643	807	657	643	692	745	1066
1.65	761	680	756	681	760	798	715	706	812	708	685
1.7	615	771	752	715	696	696	774	724	747	701	690

TABLE 3. Mean results comparison *f(28)*

a/b	0.1	0.15	0.2	0.25	0.3	0.35	0.4	**0.45**	0.5	0.55	0.6
1.3	1786	1783	1789	1823	1966	1958	1943	1933	1969	1973	1942
1.35	1774	1787	1784	1774	1808	1944	1911	1941	1965	1965	1956
1.4	1797	1797	1768	1771	1771	1817	1937	1922	1923	1936	1935
1.45	1803	1769	1781	1780	1777	1759	1773	1940	1941	1904	1922
1.5	1776	1766	1771	1789	1768	1783	1759	**1727**	1950	1915	1914
1.55	1774	1774	1775	1768	1753	1755	1778	1756	1744	1968	1889
1.6	1754	1766	1763	1764	1746	1762	1766	1762	1771	1762	1928
1.65	1773	1769	1754	1753	1759	1765	1773	1781	1757	1763	1772
1.7	1785	1801	1774	1761	1740	1748	1755	1754	1757	1756	1762

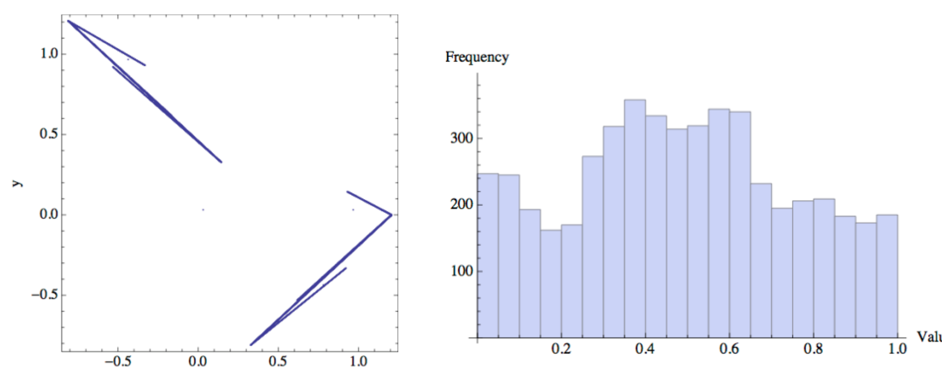

FIGURE 2. (left) *x*,*y* plot of the tuned Lozi map; (right) CPRNG based on tuned Lozi map – distribution histogram transferred into the range ⟨0, 1⟩ (15000 samples)

CONCLUSION

In this paper the extensive tuning experiment of Lozi Chaotic embedded into PSO algorithm map was presented. The controlling parameters of Lozi Chaotic map were set to different values and the impact on the performance of chaotic PSO algorithm was observed. The presented results support claim that different settings of chaotic map leads to significantly different CPRNG attributes and subsequently has great effect on the performance of chaotic PSO algorithm. It seems that the most promising values for parameter *a* are 1.4-1.5 and for parameter *b* 0.35 – 0.45. As can be observed from the results the impact of different CPRNG settings may be very dramatic in some cases (*f(2), f(15)*). In the future research the focus will be on the dynamic of differently set CPRNG and its interaction with the PSO inner dynamics.

ACKNOWLEDGMENTS

This work was supported by Grant Agency of the Czech Republic - GACR P103/13/08195S, Grant of SGS No. SP2014/159 VŠB - Technical University of Ostrava, Czech Republic, by the Development of human resources in research and development of latest soft computing methods and their application in practice project, reg. no. CZ.1.07/2.3.00/20.0072 funded by Operational Programme Education for Competitiveness, co-financed by ESF and state budget of the Czech Republic, by European Regional Development Fund under the project CEBIA-Tech No. CZ.1.05/2.1.00/03.0089 and by Internal Grant Agency of Tomas Bata University under the project No. IGA/FAI/2014/010.

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