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A Dissipative Particle Swarm Optimization

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Abstract - A dissipative particle swarm optimization is developed according to the self-organization of dissipative structure. The negative entropy is introduced to construct an opening dissipative system that is far-from-equilibrium so as to driving the irreversible evolution process with better fitness. The testing of two multimodal functions indicates it improves the performance effectively.

1. Introduction

Particle swarm optimization (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart in 1995 [1, 2]. The underlying motivation for the development of PSO algorithm was social behavior of animals such as bird flocking, fish schooling, and swarm theory [3]. One of reasons that PSO is attractive is that there are very few parameters to adjust. Work presented in [4, 5] describes the complex task of parameter selection in the PSO model. Several researchers have analyzed the performance of the PSO with different settings, e.g., neighborhood settings [6], cluster analysis [7], etc. It has been used for approaches that can be used across a wide range of applications [8].

However, studies by Angeline [9] showed that although PSO discovered reasonable quality solutions much faster than other evolutionary algorithms, it did not possess the ability to improve upon the quality of the solutions as the number of generations was increased. This indicates although the current simple social model in PSO suggests the irreversible process toward higher fitness by the weak selection that recording best historical experience, it is lacking of enough capability to "sustainable development" (i.e. get better fitness as evolution process goes on).

Understanding the emergence and evolution of biological and social order has been a fundamental goal of evolutionary theory. Current rapid development of methods of complex systems dynamics [10-13] argue that order can only be maintained by *self-organization*. Structures of increasing complexity in open systems based on energy exchanges with the environment were developed into a general thermodynamic concept of *dissipative structures* by Prigogine [10]. With the selection that providing the direction of evolution, the self-organization of dissipative systems interprets the general phenomenon of a nonequilibrium system evolving to an order state as a result of fluctuations.

Self-organizing dissipative systems allow adaptation to the prevailing environment, i.e. they react to changes in the environment with a thermodynamic response which makes the systems extraordinarily flexible and robust against perturbation of the outer conditions. An entirely new technology will have to be developed to tap the high guidance and regulation potential of self-organizing systems for technical processes. The superiority of self-organizing systems is illustrated by biological and social systems where complex products can be formed with unsurpassed accuracy, efficiency and speed.

This paper describes a variant of particle swarm, termed *dissipative* PSO, which introduces negative entropy to stimulate the model in PSO operating as a dissipative structure. Both standard and dissipative versions are compared on two multimodal optimization problems typically used in evolutionary optimization research. The results show that the additional fluctuations supply some advantage to particle swarm on " sustainable development" .

2. Standard particle swarm optimization (SPSO)

The fundament to the development of PSO is a hypothesis [14] that social sharing of information among conspeciates offers an evolutionary advantage. PSO is similar to the other evolutionary algorithms in that the system is initialized with a population of random solutions. However, each potential solution is also assigned a randomized velocity, and the potential solutions, call *particles*, corresponding to individuals. Each particle in PSO flies in the D-dimensional problem space with a velocity which is dynamically adjusted according to the flying experiences of its own and its colleagues. The location of the *i*th particle is represented as $X_i = (x_{i1},\dots, x_{id}, \dots, x_{iD})$, where $x_{id} \in [l_d, u_d]$, $d \in [1, D]$, l_d, u_d are the lower and upper bounds for the *d*th dimension, respectively. The best previous position (which giving the best fitness value) of the *i*th particle is recorded and represented as $P_i = (p_{i1},\dots, p_{id}, \dots, p_{iD})$, which is also called *pbest*. The index of the best particle among all the particles in the population is represented by the symbol *g*. The location P_g is also called *gbest*. The velocity for the *i*th particle is represented as $V_i = (v_{i1},\dots, v_{id}, \dots, v_{iD})$, is clamped to a maximum velocity $V_{max} = (v_{max,1},\dots, v_{max,d}, \dots, v_{max,D})$, which is specified by the user.

The particle swarm optimization concept consists of, at each time step, changing the velocity and location of each particle toward its *pbest* and *gbest* locations according to the equations (1a) and (1b), respectively:

$$v_{id} = w * v_{id} + c_1 * rand() * (p_{id} - x_{id}) + c_2 * rand() * (p_{gd} - x_{id}) \quad (1a)$$

$$x_{id} = x_{id} + v_{id} \quad (1b)$$

Where w is inertia weight [15], c_1 and c_2 are acceleration constants [8], and *rand*() is a random function in the range [0, 1]. For equation (1a), the first part represents the inertia of pervious velocity; the second part is the " cognition" part, which represents the private thinking by itself; the third part is the "social" part, which represents the cooperation among the particles [16]. If the sum of accelerations would cause the velocity v_{id} on that dimension to exceed $v_{max,d}$, then v_{id} is limited to $v_{max,d}$. V_{max} determines the resolution with which regions between the present position and the target position are searched [4, 8].

The process for implementing PSO is as follows:

a). Initialize a population (array) which including *m* particles, For the *i*th particle, it has random location X_i in the problem space and for the *d*th dimension of velocity V_i, $v_{id} = Rand_2() * v_{max,d}$, where $Rand_2()$ is in the range [-1, 1];

b). Evaluate the desired optimization fitness function for each particle;

c). Compare the evaluated fitness value of each particle with its *pbest*. If current value is better than *pbest*, then set the current location as the *pbest* location. Furthermore, if current value is better than *gbest*, then reset *gbest* to the current index in particle array;

d). Change the velocity and location of the particle according to the equations (1a) and (1b), respectively;

e). Loop to step b) until a stop criterion is met, usually a sufficiently good fitness value or a predefined maximum number of generations G_{max}.

The parameters of standard PSO includes: number of particles m, inertia weight w, acceleration constants c_1 and c_2, maximum velocity V_{max}.

3. Dissipative particle swarm optimization (DPSO)

3.1 Self-organization of dissipative structures

Three realms of thermodynamics are differentiated by Prigogine [10, 12]. In equilibrium realm, it has maximal entropy. Close to equilibrium realm, where the rates of processes are linear functions of the underlying forces, systems evolve toward a stationary equilibrium state characterized by the minimum of entropy production compatible with the boundary conditions. In the third, far-from-equilibrium realm of thermodynamics, with the nonlinearity of flows and forces, system leaves the unstable state and evolves to one of the many possible new states. These new states can be highly organized states. The features of far-from-equilibrium systems imply that initial conditions and random fluctuations may have a permanent effect on the system's development. Since the creation of organized nonequilibrium states are due to dissipative processes, they are called dissipative structures.

The self-organization of dissipative structure is frequently used as a generic dynamic concept to describe the evolution of nonlinear systems [11, 12, 17]. Often, such applications do not even refer to the thermodynamic foundations, but far-from-equilibrium conditions are taken for granted as a prerequisite for developing increasingly complex structures in evolutionary processes.

Moreover, self-organization requires a system consisting of multiple elements in which nonlinear relations of feedback between system elements are present [13, 17]. Positive feedback is necessary for the amplifying of random fluctuations so as to drive the dissipative system into an order state distinguishable from the random configuration of thermodynamic equilibrium. In order to maintain the order state, some negative feedback is also present that dampen the effects of further fluctuations. Self-organization thus results from interplay of positive and negative feedback, which of these is actually realized depends on random fluctuations. Therefore, system development is permanently affected by random fluctuations. Accordingly, the Prigogine school refers to the self-organization of dissipative systems as "order through fluctuations" [11, 12].

With the spatiotemporal symmetry broking by selection for higher fitness, the self-organization of dissipative structure provides the inevitability of the general phenomenon of increasingly complex structures in a nonequilibrium system out of chanciness.

3.2 Social model in standard PSO

The simple social model in standard PSO has some characteristics for self-organization of dissipative structure. The selection of keeping best historical experience constructs the irreversible process toward higher fitness. Then the process starts as the initialization of particles with random locations and velocities bring the system far-from-equilibrium. The randomicity of fluctuations is provided by the *rand*() function for the acceleration constants. The "social" part of equation (1a) ensures non-linear relations of positive and negative feedback between particles according to the cooperation and challenge with the particle with best experience so far.

However, these characteristics that similar to dissipative structure may be faded as evolution process goes on.

Firstly, as the function of successive negative feedback by imitating the best particle among all the particles (*gbest*), the best historical experience of every particle (*pbest*) are apt to be similarly, which means the "social" part is tend to be ineffective, and the swarm is inclined to be decomposed as independent particles which lost nonlinear relations of feedback between particles.

Secondly, the swarm may be damped to equilibrium state. In order to solve different problems, the concept of inertia weight w was introduced by Shi [15] to satisfy the requirements for different balances between the local search ability and global search ability, i.e. to be in equilibrium or in chaos. Since the chaotic state should be avoided to accelerate the evolution process, the small or time decreasing w is usually adopted [4], which will diminish the diversity of swarm and lead to equilibrium.

For an extreme case, if the particles have same locations, same *pbest*s, and all in zero velocities at certain evolution stage (for example, initialization stage), then the swarm is in stationary equilibrium with no possibility to evolution.

3.3 Dissipative particle swarm optimization

If the swarm is going to be in equilibrium, the evolution process will be stagnated as time goes on. To prevent the trend, an opening dissipative system DPSO is constructed by introduces negative entropy through additional chaos for particles, with the following equations (2a) and (2b) that is executed after equation (1) in the step d) of SPSO.

The chaos for velocity of particle is represented as:

$$\textbf{IF}\ (rand() < c_v)\ \ \textbf{THEN}\ \ v_{id} = rand()*v_{max,d} \qquad (2a)$$

The chaos for location of particle is represented as:

$$\textbf{IF}\ (rand() < c_l)\ \ \textbf{THEN}\ \ x_{id} = Random(l_d, u_d) \qquad (2b)$$

Where c_v and c_l are chaotic factors that in the range [0, 1], When $Random(l_d, u_d)$ is a random value between l_d and u_d.

As in an opening system, the flying of a particle is not only referring to the historical experiences, but also effected by environment. The chaos introduces the negative entropy from outer environment, which will keep the system in far-from-equilibrium state. Then the self-organization of dissipative structure comes into being with the inherent nonlinear interactions in swarm and leads to " sustainable development" from the fluctuations.

This dissipative PSO model can be mapping into human social creative activity for exploring new knowledge. People accept new information from the environment frequently and get rid of general experiences consciously, found fresh knowledge space which is far from old and general one, carry through various nonlinear information sharing and competition among social members, so that new rudiment of thinking info will appear and be magnified, new knowledge then comes into being.

4. Experimental setting

In order to test the capability of the dissipative PSO to "sustainable development" , two multimodal functions that are commonly used in the evolutionary computation literature [5, 9] are used. Both functions are designed to have minima at the origin.

The function f_1 is the generalized Rastrigrin function:

$$f_1 = \sum_{d=1}^{D} (x_d^2 - 10\cos(2\pi x_d) + 10) \tag{3a}$$

The function f_2 is the generalized Griewank function:

$$f_2 = \frac{1}{4000}\sum_{d=1}^{D} x_d^2 - \prod_{d=1}^{D}\cos\left(\frac{x_d}{\sqrt{d}}\right) + 1 \tag{3b}$$

For dth dimension, $x_{max,d}$=10 for f_1; $x_{max,d}$=600 for f_2. For both functions, the initialization range $x_d \in [-x_{max,d}, x_{max,d}]$ (for equation (2b), x_{id} = $Random(-x_{max,d}, x_{max,d})$), maximum velocity $v_{max,d}=x_{max,d}$. Acceleration constants $c_1 = c_2$=2. The fitness value is set as function value. For all the figures that mentioned, the number of particles m is fixed at 20. We had 500 trial runs for every instance.

5. Results and discussion

Figure 1, 2 and figure 3, 4 shows the mean fitness value of the best particle found with different w, c_v and c_l for the Rastrigrin and Griewank function, respectively. Where $c_v=c_l$=0, i.e. no additional negative entropy, means the standard PSO version, inertia weights w are varied from 0 to 1, c_v and c_l are set as 0.001 and 0.002 for one parameter and as 0 for another parameter to test different status, G_{max} is set as 1000 and 1500 generations corresponding to the dimensions 10 and 20, respectively.

By looking at the shape of curves in these figures, it is easy to see a "balance point" for SPSO, i.e. a value of w with best mean fitness, which indicating a balance between the local and global search ability. When the w is larger than the balance value, the SPSO is going to be in chaotic state which lacking of local search ability. There has almost no difference for the performance between the standard and the dissipative PSO version. When the w is less than the balance value, the SPSO is apt to be in equilibrium state which lacking of global search ability. With the introduced negative entropy, both cases of the dissipative PSO version show excellent performance than the standard PSO version. Moreover, the chaos for location seems more effective than for velocity since it introduces large fluctuations, and is not affected by the value of inertia weight directly.

In addition, for standard PSO, it can be found an interesting phenomenon that is not according with the original anticipation [15] of decreasing performance with decreasing global search ability when w is decreasing to zero, which indicates some unclear mechanisms may exists in the variation of w that should be studied in the future.

In order to investigate whether the dissipative PSO scales well or not, different numbers of particles m are used for each function which different dimensions. The numbers of particles m are 20, 40, 80 and 160. G_{max} is set as 1000, 1500 and 2000 generations corresponding to the dimensions 10, 20 and 30, respectively. Table 1 gives the additional test conditions, where SF_0 is the results by Shi and Eberhart [5] with an asymmetric initialization method and a linearly decreasing w which from 0.9 to 0.4. SF_1 provides a transitional comparison to SF_0 as a symmetric initialization in this work. DF_2 and DF_3 are DPSO with c_v=0, c_l=0.001, and the w of DF_3 is fixed at 0.4.

Table 2 and 3 lists the mean fitness value of the best particle found for the Rastrigrin and Griewank function, respectively.

The little difference of the results between SF_0 and SF verifies that PSO were only slightly affected by the asymmetric initialization [9]. With same setting with linearly decreasing w, DF_2 is superior to SF_0 for Rastrigrin function, and is similar to SF_0 for Griewank function. However, for DF_3, which w is fixed as 0.4, it shows overwhelming superiority to SF_0 for Rastrigrin function, and is also superior to SF_0 in most cases for Griewank function. The results suggest the performance can be improved by introduce negative entropy into the dissipative system as w is small.

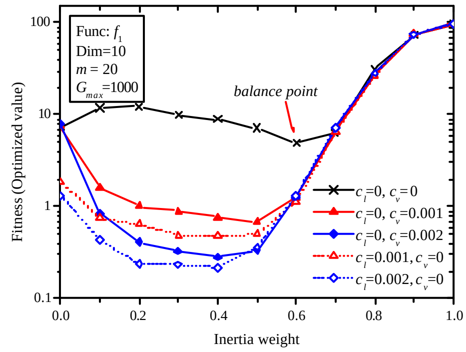

FIG. 1 10-D Rastrigrin function with different c_v and c_l

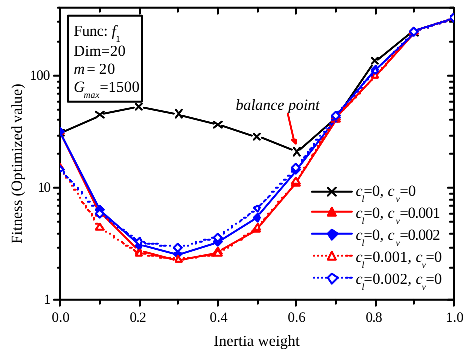

FIG. 2 20-D Rastrigrin function with different c_v and c_l

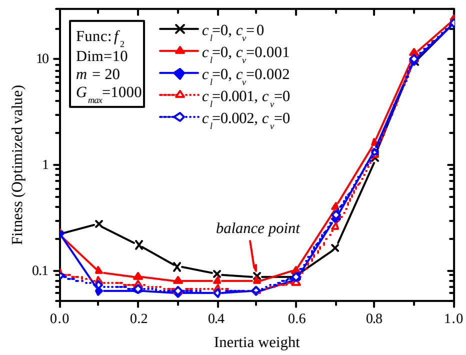

FIG. 3 10-D Griewank function with different c_v and c_l

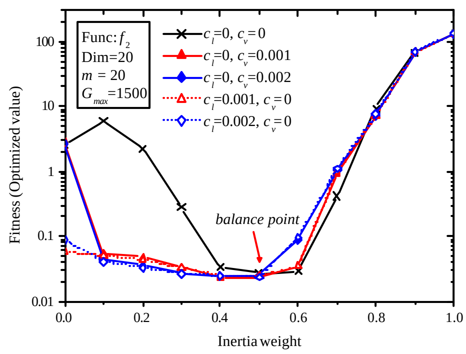

FIG. 4 20-D Griewank function with different c_v and c_l

TABLE 1: Test conditions for standard and dissipative PSO

Type	SF_0[5]	SF_1	DF_2	DF_3
PSO version	SPSO	SPSO	DPSO	DPSO
Initialization	asymmetric	symmetric	symmetric	symmetric
Inertia weight	0.9 to 0.4	0.9 to 0.4	0.9 to 0.4	0.4

TABLE 2: The mean fitness values for the Rastrigrin function

m	Dim.	G_{max}	SF_0[5]	SF_1	DF_2	DF_3
20	10	1000	5.5572	5.20620	3.08128	0.47068
	20	1500	22.8892	22.77236	13.85226	2.57289
	30	2000	47.2941	49.29417	33.11479	7.32582
40	10	1000	3.5623	3.56974	1.62999	0.07619
	20	1500	16.3504	17.29751	10.37524	1.30880
	30	2000	38.5250	38.91423	24.8981	6.21067
80	10	1000	2.5379	2.38352	0.71879	0.00796
	20	1500	13.4263	12.90195	7.25417	0.74955
	30	2000	29.3063	30.03748	19.31247	4.22646
160	10	1000	1.4943	1.44181	0.22699	0.00199
	20	1500	10.3696	10.04382	5.19949	0.20298
	30	2000	24.0864	24.51050	15.33264	2.91272

TABLE 3: The mean fitness values for the Griewank function

m	Dim.	G_{max}	SF_0[5]	SF_1	DF_2	DF_3
20	10	1000	0.0919	0.09609	0.08937	0.06506
	20	1500	0.0303	0.02856	0.02863	0.02215
	30	2000	0.0182	0.01506	0.01562	0.01793
40	10	1000	0.0862	0.08622	0.08170	0.05673
	20	1500	0.0286	0.02868	0.03085	0.02150
	30	2000	0.0127	0.01348	0.01252	0.01356
80	10	1000	0.0760	0.07669	0.06767	0.05266
	20	1500	0.0288	0.03109	0.02766	0.02029
	30	2000	0.0128	0.01374	0.01345	0.01190
160	10	1000	0.0628	0.06373	0.06246	0.05047
	20	1500	0.0300	0.03041	0.03145	0.01940
	30	2000	0.0127	0.01321	0.01260	0.01029

Figure 5 and 6 shows the mean fitness value of the best particle found during 1500 generations with different w and c_l for the Rastrigrin and Griewank function with 20 dimensions, respectively. c_v is fixed as zero. c_l are set as 0 (SPSO) or 0.001 (DPSO). The inertia weights are fixed as 0.4 or linearly decreasing from 0.9 to 0.4, respectively.

For the Rastrigrin function, it can be seen that the performance of DPSO is similar to SPSO during the early stage, however, it will sustainable evolving when the evolution of SPSO is almost stagnated. For the Griewank function, this tendency is weakly but is also exists. For both functions, when w=0.4, the performance of the SPSO is the worst; while of the DPSO is the best.

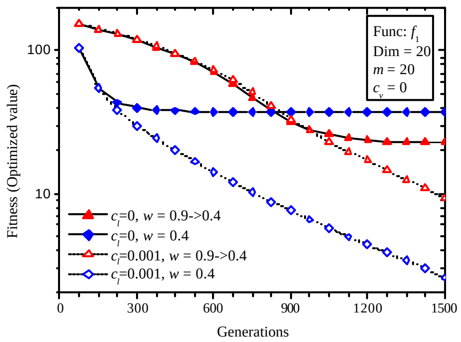

FIG. 5 20-D Rastrigrin function with different w and c_l

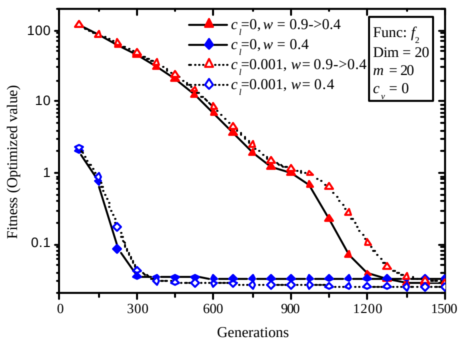

FIG. 6 20-D Griewank function with different w and c_l

6. Conclusion

Self-organizing has shown extraordinarily flexible and robust in nature systems. By introducing negative entropy into the simple social model of standard PSO through additional chaos, a reasonable open system is constructed, which is in far-from-equilibrium state. With the internal nonlinear interactions among particles, the self-organization of dissipative structure comes into being with the dissipative processes for the introduced negative entropy, which drives the irreversible evolution process toward higher fitness by the selection of keeping best experience. The testing of two multimodal benchmark functions that are commonly used in the evolutionary computation literature indicates the dissipative PSO can improve the performance efficiently.

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