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A Hybrid PSO-GSA Strategy for High-dimensional Optimization and Microarray Data Clustering*

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***Abstract*— High-dimensional data analysis and its great chances of overfitting result in great challenges for constructing efficient models in practical applications. To overcome these problems swarm intelligence algorithms can be utilized. However, the balance between global and local search throughout the course of a run is critical to the success of an intelligence optimization algorithm. Moreover, almost all the available algorithms are still having issues like premature convergence to local optimum and slow convergence rate, especially in high-dimensional space. As motivated above, a new hybrid optimization algorithm integrating particle swarm optimization(PSO) with gravitational search algorithm(GSA) is presented (denoted as PSOGSA). Based on the analysis of the compensatory advantages of the PSO and the GSA, in this paper, we integrate the ability of exploitation in PSO with the ability of exploration in GSA to update velocity equations. To update position equations a mobility factor is used which is guided by diversity of population to improve the final accuracy and the convergence speed of the PSOGSA. We also apply proposed algorithm to the cluster analysis of microarray data. Experiments are conducted on six benchmark test functions, four artificial data sets and three microarray data sets, and the results demonstrate that the proposed algorithm possess better robustness.**

***Index Terms*— local search; global search; high dimensional; clustering; microarray data.**

I. Introduction

Clustering is a widely used technique having a large number of applications in many well-known fields such as machine learning, pattern recognition, and bioinformatics. The classical clustering algorithm, such as k-means, usually struggle with high(or ultra-high) dimensional data to handle large search space. Therefore the heuristic optimization is widely used to deal with this problem[1, 2].

Compared with complete search techniques, heuristic algorithms emphasize accurate and exact computation. Approximate search algorithms are more robust and efficient methods for solving the problem with high-dimensional search space. Various heuristic approaches, including Genetic algorithm (GA)[3, 4], Ant colony optimization (ACO)[5, 6], Particle swarm optimization (PSO)[7, 8], and Gravitational search algorithm (GSA)[9], etc, have been proposed and widely applied in many areas. These algorithms are typically motivated by biological process or physical phenomenon and they are population-based stochastic optimization techniques. In case of global optimization an efficient and effective algorithm should possess two abilities namely, exploration and exploitation. The exploration is the ability of an algorithm to search whole feasible space of the problem. In contrast to exploration, the exploitation is the convergence ability to the best solution near a good solution[10]. However, one important issue is how to prevent particles from the premature convergence, e.g. being trapped in local optimum, and improve its convergence rate. Hence, hybridization of the heuristic optimization algorithms is an efficient way to solve this problem.

Implementation of PSO is less complex and it has only few parameters that are needed to be adjust, so it has been widely used in many fields, including Artificial Intelligence, Pattern Recognition and Computer Engineering, etc[11–13]. However, one drawback of the traditional PSO is that still having some typical issues as convergence to local optimum and slow convergence rate[14]. To address this problem, many hybrid mechanism combining PSO with other optimization algorithm have been presented, such as GAPSO[15], PSOACO[16] and PSO-BFGS[17],etc. A thorough study results in a conclusion that within a high-dimensional search space compared to GA, PSO, etc, the GSA gives a better performance in exploration ability and convergence rate[9] for solving global optimization problem. The balance between global and local search throughout the course of a run is critical to the success of an optimization algorithm. In PSO, the part of private thinking$(p_i(t) - x_i(t))$ has local search ability and the part of social thinking$(p_g(t) - x_i(t))$ has global search ability. In GSA, based on the overall force obtained by all other particles, particle direction is computed,

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so it has the strong ability of social thinking. In the work of Mirjalili and Hashim[18], the part of $(p_g(t) - x_i(t))$ in PSO and the part of $a(t)$ in GSA are integrated to update velocity equation, so the local search mode of the proposed algorithm would be degraded to a certain extent. In our work, however, the ability of local search in PSO and the ability of global search in GSA is integrated, and the interactive factors are proposed to improve the defect of search behavior.

Microarray data analysis is a very important task to identify differentially expressed genes in a highly parallel manner[19]. To mining the similarity expression pattern of genes, clustering has become inevitable. Several clustering algorithms have been developed and applied to analyze microarray data, such as fuzzy C-means[20], self-organizing oscillator networks[21], etc.

In this paper, we take advantage of the compensatory properties of the PSO and the GSA to propose a new algorithm that integrates the search modes of both. The velocity updated equation integrates the part of private thinking in PSO and the part of acceleration in GSA. Then the advantages of the PSO and the GSA are analyzed by benchmark test functions to obtain velocity updated equation with interactive learning strategy. Finally, we conduct two parts experiments for proposed algorithm. The first one is the effectiveness and robustness of the PSOGSA which are tested on six benchmark functions. The experimental results demonstrate that our method is significantly better than several available algorithms. The second one is, we use proposed method to clustering on two groups, namely artificial data sets and microarray data sets. Experimental results obtained for both data types demonstrate the effectiveness of our method. One can see that this new approach for microarray data analysis is highly efficient and outperforming as compare to other clustering methods in available publications.

II. A Hybrid PSO-GSA Strategy

A. Particle Swarm Optimization(PSO)

The PSO is a stochastic optimization method which is motivated by social behavior of bird flocking and developed by Dr. Eberhart and Dr. Kennedy in 1995[7]. In PSO, the potential solutions, called particles, fly in a D-dimensional space according to the historical experiences of its own and its colleagues. At the tth iteration, the velocity and the position of the ith particle are updated for its dth dimension as follows:

$$v_i^{(d)}(t+1) = wv_i^{(d)}(t) + c_1 r1_i^{(d)}\left(p_i^{(d)}(t) - x_i^{(d)}(t)\right) + c_2 r2_i^{(d)}\left(p_g^{(d)}(t) - x_i^{(d)}(t)\right)$$

$$x_i^{(d)}(t+1) = x_i^{(d)}(t) + v_i^{(d)}(t+1), i \in \{1, 2, \cdots, N\}$$

Where w is inertia weight that makes a tradeoff between the global and local search abilities, the c_1 and c_2 are acceleration constants, the $r1 \in [0, 1]$ and $r2 \in [0, 1]$ are uniform random numbers.

B. Gravitational Search Algorithm(GSA)

The GSA is also a novel population-based search algorithm proposed by E. Rashedi et.al in 2009[9], based on the law of Gravity and the notion of mass interactions. In GSA, each particle could observe the performance of the others. A heavy mass has a large effective attraction radius which denote a great intensity of attraction define gravitation force which is a an information-transferring tool. Therefore, particles with a better performance have a greater gravitational mass. As a result, the particles tend to move toward the best particle. Now, we consider a system with N particles, the position of the ith particle is defined by:$X_i = \left(x_i^{(1)}, x_i^{(2)}, \cdots, x_i^{(n)}\right), i \in \{1, 2, \cdots, N\}$.

The updated equation of the velocity and the position of particles are listed as follows:

$$v_i^{(d)}(t+1) = r_i v_i^{(d)}(t) + a_i^{(d)}(t)$$

$$x_i^{(d)}(t+1) = x_i^{(d)}(t) + v_i^{(d)}(t+1), i \in \{1, 2, \cdots, N\}$$

Where $a_i^{(d)}(t)$ is the acceleration of the particle i at the tth time in direction dth , and can be calculated by

$$a_i^{(d)}(t) = \frac{F_i^{(d)}(t)}{M_{ii}(t)}$$

Where M_{ii} is the inertial mass of ith particle.

$$F_i^{(d)}(t) = \sum_{j=1, j\neq i}^{N} r_j F_{ij}^{(d)}$$

where r_j is a random number in the interval [0,1] and $F_i^{(d)}$ is the force acting on mass i from mass j,

$$F_{ij}^{(d)} = \mathrm{G}(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^{(d)}(t) - x_i^{(d)}(t)\right),$$

Where $i, j \in \{1, 2, \cdots, N\}$, $G(t)$ is gravitational constant at tth time, $R_{ij}(t)$ is the Euclidian distance between two particles i and j, and ε is a small constant.

C. The Hybrid PSO-GSA Strategy

To date, although numerous swarm intelligence algorithms have been proposed, premature convergence is still the main deficiency when solving high-dimensional and multimodal problems. Firstly, we illustrate the three main differences between GSA and PSO.

- The PSO uses a kind of memory for updating the velocity. While the GSA is memory-less and only the current position of the particle plays an important role in the updating procedure.
- The velocity and position of the PSO is updated without considering the quality of solutions of all other particles,

TABLE I

RESULTS OF GIVEN TESTED FUNCTIONS ON 10-DIMENSIONAL,THE SIZE OF POPULATION IS SET 30 AND THE MAXIMUM ITERATION IS SET 1E3

Function(initial value)	Method	#630	#1000
Sphere(2.81E3)	PSO	2.38E-23	2.37E-24
	GSA	2.02E-10	5.66E-18
Griewank(1.55E1)	PSO	3.48	3.49
	GSA	1.19E-5	3.36E-9

TABLE II

RESULTS OF BENCHMARK TEST FUNCTIONS ON 10-DIMENSIONAL AND 60-DIMENSIONAL, THE SIZE OF POPULATION IS SET 30 AND THE MAXIMUM ITERATION IS SET 1E3

	10-D		60-D	
Function	GSA	PSO	GSA	PSO
Sphere	7.96E-18	**2.21E-39**	**1.70E-15**	8.36
Ackley	3.43E-9	**3.55E-15**	**1.96**	2.34
Weierstrass	1.35E-4	**0**	**3.26E-1**	9.9
E_SchafferF6	1.66	**1.52E-1**	**1.16E1**	2.52E1

it has a strength local search abilities while the velocity and position of the GSA is calculated based on the overall solution, so it has a strength global search ability. This conclusion can be obtained by TABLE I. the experiments are conducted on Sphere's function and Griewank's function. From the TABLE I, we can see that the PSO shows fast convergence when iteration reach to 630, and get trapped into local optimal. However, the GSA has global search ability to avoid trapping to local optimum.

- The PSO displays high performance for low dimensional problems whereas the GSA show better performance for high dimensional problems. This conclusion can be obtained by TABLE II. The GSA and the PSO are tested on Spheres function, Ackleys function Weierstrasss function and Expanded Schaffer function 6:

Taking into consideration all the above reasons, we take advantages of the compensatory property of the PSO and the GSA to integrate a hybrid algorithm, PSOGSA. The velocity of the dth dimension of the ith particle is updated by the following equations:

$$v_i^{(d)}(t+1) = wv_i^{(d)}(t) + c_1 r1_i^{(d)}\left(p_i^{(d)}(t) - x_i^{(d)}(t)\right) + c_2 r2_i^{(d)} a_i^{(d)}(t)$$

where c_1 and c_2 are time varying interactive learning factors. the $r1$ and $r2$ are random numbers in the range belong to [0,1].

To ensure that the particle has adaptive mobility in the later stages, this paper proposed the diversity of population guiding momentum factor to change, and the position updated equation is modified as follows:

$$x_i^{(d)}(t+1) = \rho \cdot x_i^{(d)}(t) + v_i^{(d)}(t+1), i \in \{1, 2, \cdots, N\}.$$

where ρ is an adaptive momentum factor, $\rho = \left(\frac{1}{1+\exp(Div)}\right) \cdot \frac{5}{4}$, the diversity of population Div can be calculated by

$$Div = \frac{\prod_{i=1}^{N} [|a_i - x_i| + |pbest_i - x_i|]}{N(up - low)}$$

where up and low is upper and lower bound of the search space, respectively

D. Time varying interactive learning factors

For the success of an optimization algorithm the balance between global and local search is critical[10, 22]. In PSOGSA, for a certain dimension, if the $p_i(t)$ and $a_i(t)$ are on opposite sides of the particles current position $x_i(t)$, the $p_i(t)$ and $a_i(t)$ may make the particle oscillate. However, the $a_i(t)$ is more likely to provide a larger momentum, as $a_i(t)$ is likely to be larger than the$|p_i(t) - x_i(t)|$. Hence, the $a_i(t)$ may influence the particle to move in its direction even if it is in a local optimum region far from the global optimum. If the $p_i(t)$ and $a_i(t)$ are on the same side of the particles current position $x_i(t)$, the particle will move in that direction and it may be impossible to jump out of the local optimum once its $p_i(t)$ fall into the same local optimum region where the $a_i(t)$ is. However, in our learning strategy, interactive learning is applied to update the velocity equation. The mathematical formula of $c_i(t)$ and $c_i(t)$ at the ith iteration are following:

$$c_1(t) = 1 - \exp\left(-30 \cdot \left(\frac{t}{maxIter}\right)^{\alpha}\right)$$

$$c_2(t) = \exp\left(-30 \cdot \left(\frac{t}{maxIter}\right)^{\beta}\right)$$

Where $maxIter$ is maximum iterations. In premier iterations, to avoid trapping in a local optimum, the algorithm must explore the search space to find new solutions. Hence, in PSOGSA, the factor c_2 is larger than c_1. By lapse of iterations, exploration fades out and exploration fades in, therefore, the c_1 is larger than c_2(see Fig. 1).

III. EXPERIMENTS

In this section, we conduct two groups experiments for proposed algorithm, six benchmark functions optimization and microarray data analysis on three data sets.

A. Experiments on benchmark functions

In order to demonstrate that the proposed algorithm perform well in different dimensions, experiments are conducted to compare three algorithms including the PSOGSA algorithm on six test functions with 30-dimensional and 60-dimensional.

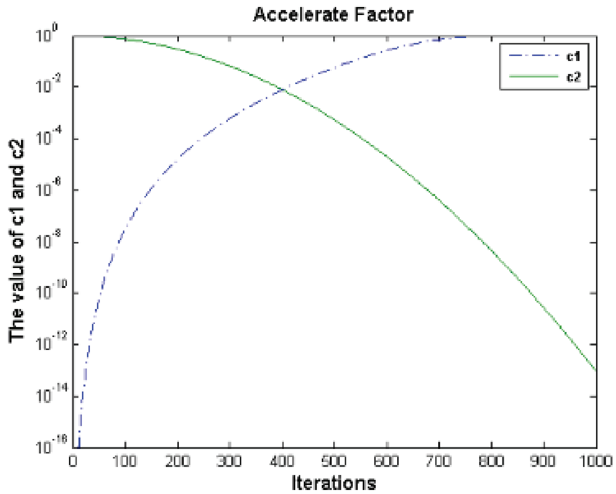

Fig. 1. The interactive learning factors, c_1 and c_2 when $\alpha = 9$ and $\beta = 2$.

TABLE III
THE RESULTS OF SIX BASIC BENCHMARK FUNCTIONS WITH 30-DIMENSIONAL

Function	GSA	PSO	PSOGSA	Optimum
F1(Sphere)	3.74E-17	3.97E-08	**2.02E-180**	0
F2(Rosenbrock)	**2.61E+01**	2.95E+02	2.83E+01	0
F3(Weierstrass)	7.45E-04	2.32E-01	**0**	0
F4(Rastrigin)	5.69E+00	1.39E-02	**0**	0
F5(Ackley)	8.14E-09	1.88E-01	**0**	0
F6(Griewank)	2.50E-05	1.80E+02	**0**	0

TABLE III and IV demonstrate the comparison of our purposed method (PSOGSA) and individual performances of PSO and GSA. One can see from these tables that performance of our method leads to optimal solution for several basic benchmark functions for both 30-dimensional and 60-dimensional. We observe that out of 6 functions 4 functions give exact optimal solution for both dimensions while PSO and GSA could not provide optimal results. The PSOGSA surpasses all other algorithms on from function 3 to function 6 which expose the highly efficient performance of PSOGSA.

B. PSOGSA for microarray data clustering

In this section, we conduct four clustering algorithm-s, namely k-means, PSO clustering, GSA clustering, P-SOGSA clustering, which are tested on four artificial da-ta sets (see Fig.2) and three cancer data sets (download from http://archive.ics.uci.edu/ml/datasets.html). The descrip-tion of test data sets in detail can be found in TABLE V.

TABLE VI shows the comparison of performance among three clustering methods and PSOGSA for clustering. Com-parison is evaluated on the bases of accuracy and mutual information obtained by four methods including PSOGSA.

TABLE IV
THE RESULTS OF SIX BASIC BENCHMARK FUNCTIONS WITH 60-DIMENSIONAL

Function	GSA	PSO	PSOGSA	Optimum
F1(Sphere)	1.70E-15	2.45E+00	**2.10E-176**	0
F2(Rosenbrock)	**5.66E+01**	1.07E+02	5.88E+01	0
F3(Weierstrass)	1.16E+00	6.68E+00	**0**	0
F4(Rastrigin)	3.16E+01	4.89E-01	**0**	0
F5(Ackley)	3.26E+00	2.33E+00	**0**	0
F6(Griewank)	1.61E-01	1.91E+03	**0**	0

TABLE V
TEST DATA SETS IN OUR WORK

	Dataset Name	Sample	Feature	Class
Artificial Dataset	Artificial Dataset 1	582	2	2
	Artificial Dataset 2	243	2	2
	Artificial Dataset 3	657	2	2
	Artificial Dataset 4	432	2	2
Cancer Dataset	Breast Cancer	683	10	2
	Colon Cancer	62	2000	2
	Leukemia	38	7129	2

Datasets used for experiment are clearly shown in TABLE V. We used four artificial and three cancer datasets in our experiment. One can see from table 4 that accuracy given by PSOGSA is highest as compare to all other clustering algo-rithms for all datasets except for artificial dataset 1. Similarly we also compared the mutual information values obtained by PSOGSA and other methods. Results show that highest information values can be obtained by our method for all data sets. For example for colon cancer mutual information values given by k-means, PSO and GSA are 0.0233,0.0232 and 0.0127 respectively, while mutual information obtained by PSOGSA is 0.0598, which is highest among all values obtained by other methods. These results indicate the noble performance shown by PSOGSA.

IV. CONCLUSION

Based on the merits of both PSO and GSA, in this paper, we integrate the exploitation ability of component in PSO with the exploration ability of component in GSA. A hybrid algorithm PSOGSA synthesizes the ability of local search in PSO and the ability of global search of GSA, where individu-als enhance themselves based on social interactions and their private cognition. From results of numerical experimentation, although the PSOGSA is not better performance for all test problems in real-parameter optimization, it is superior to the other methods in the ability to finding the global optimum for most. In addition to function evaluation, our algorithm can also be used for clustering analysis, efficiently. Cluster analysis of microarray data performed by PSOGSA is

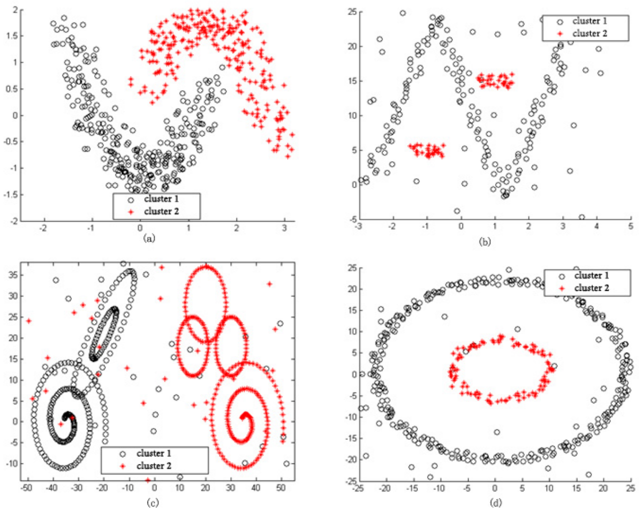

Fig. 2. Artificial Dataset. (a)Artificial Dataset 1 (b)Artificial Dataset 2 (c)Artificial Dataset 3 (d)Artificial Dataset 4.

TABLE VI
A COMPARISON OF FOUR CLUSTERING ALGORITHMS FOR ARTIFICIAL FOUR DATA SETS AND THREE CANCER DATA SETS

Dataset	Algorithm	Accuracy	Mutual Information
Artificial Dataset 1	k-means	0.9261	0.6255
	PSO	**0.9296**	0.6368
	GSA	0.9261	0.6255
	PSOGSA	0.9278	**0.6484**
Artificial Dataset 2	k-means	0.5062	3.61E-05
	PSO	0.5062	3.61E-05
	GSA	0.5103	1.00E-04
	PSOGSA	**0.5967**	**0.0093**
Artificial Dataset 3	k-means	**0.933**	**0.6443**
	PSO	**0.933**	**0.6443**
	GSA	**0.933**	**0.6443**
	PSOGSA	**0.933**	**0.6443**
Artificial Dataset 4	k-means	0.5046	1.38E-04
	PSO	0.5046	4.65E-05
	GSA	0.5046	3.50E-06
	PSOGSA	**0.5069**	**3.57E-04**
Colon Cancer	k-means	0.5484	0.0233
	PSO	0.5806	0.0232
	GSA	0.5161	0.0127
	PSOGSA	**0.6774**	**0.0598**
Breast Cancer	k-means	0.9605	0.7429
	PSO	0.9561	0.7223
	GSA	0.9619	0.7502
	PSOGSA	**0.9693**	**0.7894**
Leukemia	k-means	0.5263	0.0085
	PSO	0.5	4.33E-04
	GSA	0.5	0.0041
	PSOGSA	**0.6842**	**0.0152**

highly efficient as compare to other clustering algorithms. We conducted experiments on several data sets for the evaluation of our method. Experimental results show the high accuracy given our method as compare to other popular clustering methods. This study also can be extended to binary coding problems to solve optimization problems in real-life.

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