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An improved Particle Swarm Optimization

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Abstract

Adaptive inertia weight is proposed to rationally balance the gobal exploration and local exploration abilities for particle swarm optimization. The result algorithm is called inertia particle swarm optimization (AIW-PSO). To avoid the premature convergence caused by basic Particle Swarm Optimization (PSO). a new particle Swarm Optimization algorithm with adaptive inertia weight (AIW –PSO) is proposed. Inertia weight is adaptively changed according to the algorithm. This paper describes a method for improving the final accuracy and the convergence speed of Particle Swarm Optimization (PSO) by adapting its inertia factor in the velocity updating equation and also by adding a new coefficient. In order to demonstrate the effectiveness of AIW-PSO, comprehensive experimental were conducted on three well-known benchmark functions.

Key word: PSO, Inertia weight, Benchmark functions

1.Introduction:

As product and engineering desing becomes more and more complicated, the objective function of optimization design is increasingly high dimensional, non-convex, and highly nonlinear. Traditional optimization design method usually operate difficultly and ineffectively, easily obtain local optimal. Therefore, finding a simple optimization method that can obtain global optimal quickly and effectively has an important significance to engineering design optimization.

In recent years, with the development and widely application of evolution algorithm and intelligent algorithm, particle swarm optimization (PSO) has been proven to be a better global optimization method with simple operation and parallel search.

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In population-based optimization methods, proper control of global exploration and local exploitation is crucial in finding the optimum solution efficiently . Shi and Eberhart introduced the concept of inertia weight to the original version of PSO, in order to balance the local and global search during the optimization process.

1.1 **Some significant variants of the classical PSO**

Since its introduction by Kennedy and Eberhart in 1995, PSO has been subjected to empirical and theoretical investigations by several researchers. Shi and Eberhart introduced a new parameter ω , now well-known as *inertia weight*, to the original version of PSO in the following way:

$$V_{i,d}(t)=\omega.V_{i,d}(t-1)+c_1*rand_1*(pbest_{i,d}-x_{i,d}(t-1))+ c_2*rand_2*(gbest_d-x_{i,d}(t-1))...(1)$$

The inertia weight is used to balance the global and local search abilities. A large inertia weight is more appropriate for global search and a small inertia weight facilitates local search.

1.2 The Inertia-adaptive PSO Algorithm

Premature convergence occurs when the positions of the most of the particles of the swarm stop changing over successive iterations although the global optimum remains undiscovered. This may happen if the swarm uses a small inertia weight or a constriction coefficient. From the basic equations of PSO, we see that if $v_{i,d}$ is small and in addition to that $|pbest_{i,d} - x_{id}|$ and $|gbest_d - x_{id}|$ are small enough, $v_{i,d}$ cannot attain a Largevalue in the upcoming generations. That would mean a loss of exploration power. This can occur even an early stage of the search process, when the particle itself is the global best causing $|pbest_{i,d} – x_{i,d}|$ and $|gbest_d – x_{i,d}|$ to be zero and, gets damped quickly with the ratio ω . Also the swarm suffers from loss of diversity in later generations if *pbest* and *gbest* are close enough.

In this work we incorporate two modifications into the classical PSO scheme which prevent false convergence and helps provide excellent quality of final result without imposing any serious burden in terms of excess number of function evaluations (FEs). The first of these modifications involves modulation of the inertia factor ω according to distance of the particles of a particular generation from the global best. The value of ω for each particle is given by:

$$\omega = \omega_0 . (1-(dist_i / max\_dist)) \; .... (2)$$

where ω_0 (0.5,1) , $dist_i$ is the curredcnt Euclidean distance of *i*-th particle from the global best i. e.

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$dist_i = (\sum_{d=1} (gbest_d - x_{i,d})^2)^{1/2}$ ....(3)

and max_*dist* is the maximum distance of a particle from the global best in that generation i.e.

$max\_dist = \arg_i \max(dist_i)$ ....(4)

This modulation of the inertia factor ensures that in case of particles that have moved away from the global best, the effect of attraction towards global best will predominate. To avoid premature convergence this we must ensure that the particle has mobility in the later stages. In order to achieve our purpose, the position update equation is modified as follows:

$X_{i,d}(t) = (1 - \rho).\ X_{i,d}(t-1) + V_{i,d}(t)$ ....(5)

where ρ is a uniformly distributed random number in the range (-0.25, 0.25). From now on, we shall refer to this new algorithm as IAPSO (Inertia-adaptive PSO).

2. Experimental Results

Table1.Benchmark functions

Name of the functions	**Mathematical representation**	**Range of search**	**Range of initialization**	**Vmax**
Sphere function	$f_1(x) = \sum_{i=1}^{n} x_i^2$	$(-100,100)^n$	$(50,100)^n$	100
Rosenbrock function	$f_2(x) = \sum_{i=1}^{n} [100(x_{i+1-}\ x_i^2)^2 + (x_i - 1)^2]$	$(-100,100)^n$	$(15,30)^n$	100
Rastrigrin function	$f_3(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x) + 10]$	$(-10,10)^n$	$(2.56,5.12)^n$	10

population size=50 ,Iteration=500, dimension=10

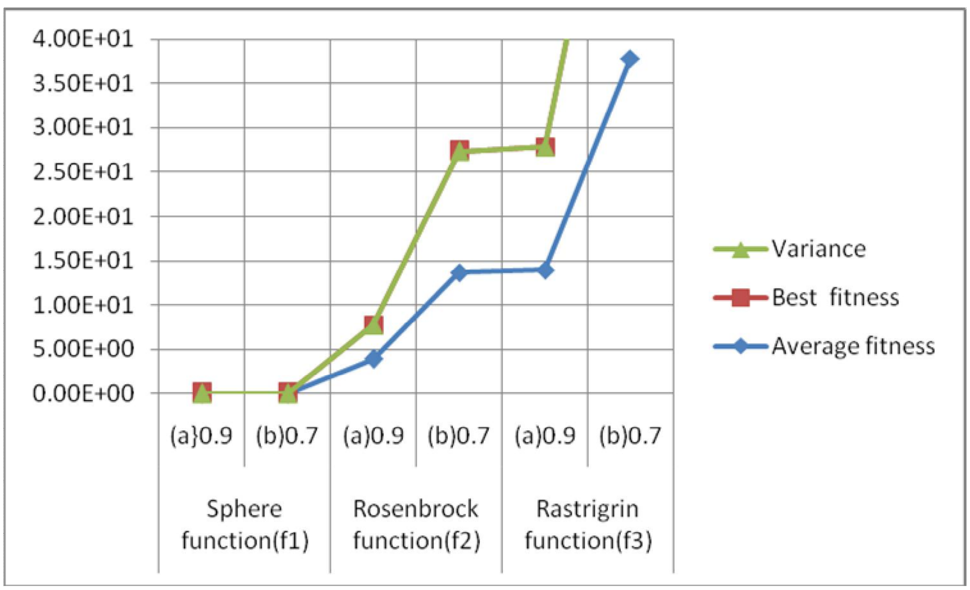
Table2.Various factors based on inertia weight

Name of the function	**Inertia weight**	**Average fitness**	**Best fitness**	**Variance**

Sphere function(f1)	(a}0.9 (b)0.7	2.0261519E-8 5.2666E-7	2.0261043E-8 5.2666E-7	3.6022766E-14 2.8215297E-16
Rosenbrock function(f2)	(a)0.9 (b)0.7	3.8576868 13.6800995	3.8566718 13.680098	2.562219E-5 7.944004E-7
Rastrigrin function(f3)	(a)0.9 (b)0.7	13.929418 37.808346	13.929418 37.808346	6.686148E-11 3.9099223E-15

The inertia weight is mainly used to improve local and global search facilities. The best fitness value can be changed according to the inertia weight . the inertia weight has been reduced the best fitness value has been increased. To improve optimizatiopn , the population value can be adjusted based on inertia weight

Graph 1:



3.Conclusion

This paper describes a method for improving speed and optimize the performance in local and global exploration for PSO. By this fair strategy, dynamically adjusted inertia weight, the performance of PSO algorithm could be improved. The experiments were conducted using different bench mark functions with various dimensions.

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