ISSN: 2414-1895 DOI: 10.6919/ICJE.202206_8(6).0089

Research and Testing of Adaptive Particle Swarm Optimization

Zhengyang Su, Lei Ni, Xiaoyu Li

Chengdu Technological University, Chengdu 610000, China

Abstract

In this paper, we aim at the problem of rapid loss of population diversity encountered in the application of PSO algorithm. A feedback strategy is proposed to maintain population diversity. In order to balance detection and development capabilities, the adjustment of inertia weights is also studied, and a new adaptive particle swarm optimization algorithm is proposed. Through the iterative comparison test of APSO algorithm and LDW algorithm, it is confirmed that APSO has higher robustness and accuracy.

Keywords

Particle Swarm Optimization; Inertia Weights; Adaptive Particle Swarm; Optimization Algorithms.

1. Introduction

Particle Swarm Optimization(PSO),is an optimization algorithm proposed by Kennedy and Eberhart in 1995[1].The application of particle swarm algorithm extends from the initial function optimization to the present neural network training, image processing, process optimization in the field of engineering, solution of stochastic optimization problems, optimal control, etc[2].As society develops and technology advances, people usually have the need to solve more complex optimization problems, so there are many scholars who improve the standard particle swarm algorithm from different perspectives[3]. For example, de Campos Jr et al. proposed a parallel multiple swarm PSO strategy for a multi-objective optimization problem, which was solved using an algorithm with a multi-cluster two-particle swarm parallel strategy [4].In order to solve complex problems of different forms, Daqing Wu et al. proposed a parallel particle swarm optimization algorithm based on hybrid policy adaptive learning [5].The PSO does not rely on the natural evolution of individuals, but simulates the social behavior of biological groups. The PSO is a simulation of this social behavior, i.e., it makes use of the information sharing mechanism so that individuals can learn from each other's experience and thus promote the development of the whole group.

One of the main problems encountered in the application of the PSO is the rapid loss of population diversity. For this problem, researchers have proposed strategies such as change of neighborhood particle topology, reproduction and offspring, adding Gaussian variational operators, spatial particle expansion, attraction and repulsion, etc. These different strategies can be grouped into two categories of ideas feedforward and feedback.

Direct control of the parameters of the PSO algorithm to maintain population diversity is a feed-forward strategy. The feedback strategy is based on the diversity measurement function of the population evolution process. Since the feedback strategy can monitor the evolutionary information at any time, it is more effective than feedforward to maintain population diversity by introducing feedback for complex systems. The second strategy, i.e., the feedback strategy to maintain population diversity, is investigated here.

In order to balance detection and exploitation capabilities, a new adaptive particle swarm optimization (APSO) was established by adjusting the inertia weights in this paper. In order to test the performance of APSO, LDW, which has similar applications in various objective optimization problems, is used

ISSN: 2414-1895 DOI: 10.6919/ICJE.202206_8(6).0089

for comparison. The final results show that the APSO algorithm has higher robustness and better finding accuracy.

2. Adaptive Particle Swarm Optimization (APSO)

2.1 Population Diversity Measurements

Definition 1 :Entropy of population distribution

Dividing the current solution space of the t generation population distribution into equal regions,the count of the number of particles contained in each region is denoted as $Z_1, Z_2, \dots Z_Q$,then the probability of an individual appearing in the kth region is $p_k = Z_k / S$,k=1,2,…,Q,Sis the total number of individuals, the entropy of the population distribution at generation t is defined as follows:

$$E(t) = -\sum_{k=1}^{Q} p_k \ln p_k \tag{1}$$

From the above equation, it can be seen that the smaller E(t) is, the more uneven the population distribution is.

Definition 2 :Mean particle spacing

Let the L be the diagonal maximum length of the search space; the S and the n, as before, denote the population size and the spatial dimension, respectively.The p_{id} denotes the value of the dth dimensional coordinate of the ith particle;the $\bar{p}_d$ denotes the mean value of the dth dimensional coordinates of all particles,Then the average particle distance is defined as follows:

$$D(t) = \frac{1}{S*L}\sum_{i=1}^{S}\sqrt{\sum_{d=1}^{n}(p_{id} - \bar{p}_d)^2} \tag{2}$$

From the above equation, the mean particle size is independent of the population size, the dimensionality of the solution space and the search range in each dimension,The smaller the D(t), the more concentrated the population is.The mean particle distance and population distribution entropy vary with population diversity during the evolutionary process, while the inertia weights regulate the detection and exploitation ability of the algorithm.In the early stage of the optimization search, in order to increase the global search capability of the algorithm, the inertia weights should be incremented with the increase of population diversity e to make it more detectable, which can be called the detection phase.In the later stage of the optimization search, in order to increase the local search ability of the algorithm, the inertia weight decreases with the decrease of population diversity, making it more exploitable, which can be called the exploitation stage.The method designed according to the above principle has the function of adapting the different distribution of particles in the search process and adjusting the search direction, so it is called adaptive particle swarm optimization algorithm(APSO).

$$w(t) = AD(t) + B \tag{3}$$

Let $w_{min} \le w(t) \le w_{max}$, $D_{min} \le D(t) \le D_{max}$,then it can be deduced that:

Volume 8 Issue 6, 2022
DOI: 10.6919/ICJE.202206_8(6).0089

$$A = \frac{w_{\max} - w_{\min}}{D_{\max} - D_{\min}} \tag{4}$$

$$B = \frac{D_{\max} w_{\min} - D_{\min} w_{\max}}{D_{\max} - D_{\min}} \tag{5}$$

2.2 Mutation operation

When the population distribution entropy E(t) or the mean grain distance D(t) is less than a given value,then the population varies at a given rate of variation.The variation method is: for the ith particle configuration distributed between [0,1] with a random number r_i,if r_i is less than the given variation rate p_m,then the particle is re-initialized in the solution space,but, the optimal position found by the particle so far is still remembered, and then a new round of search for superiority is performed, and the population mutation is completed when the above mutation operation is implemented for all m particles. The start of the mutation is the beginning of the detection phase, and both E(t) and D(t) will gradually increase as the detection proceeds,When a given value is reached, the particle swarm starts to develop.No variation is performed during the development process, and as the development proceeds, the sum starts to decrease again, and when it decreases to a given value, the algorithm enters the detection phase again. The whole evolutionary process is a continuous process of detection and development until the final search for the best or the second best point.

3. Adaptive Particle Swarm Optimization Algorithm Flow

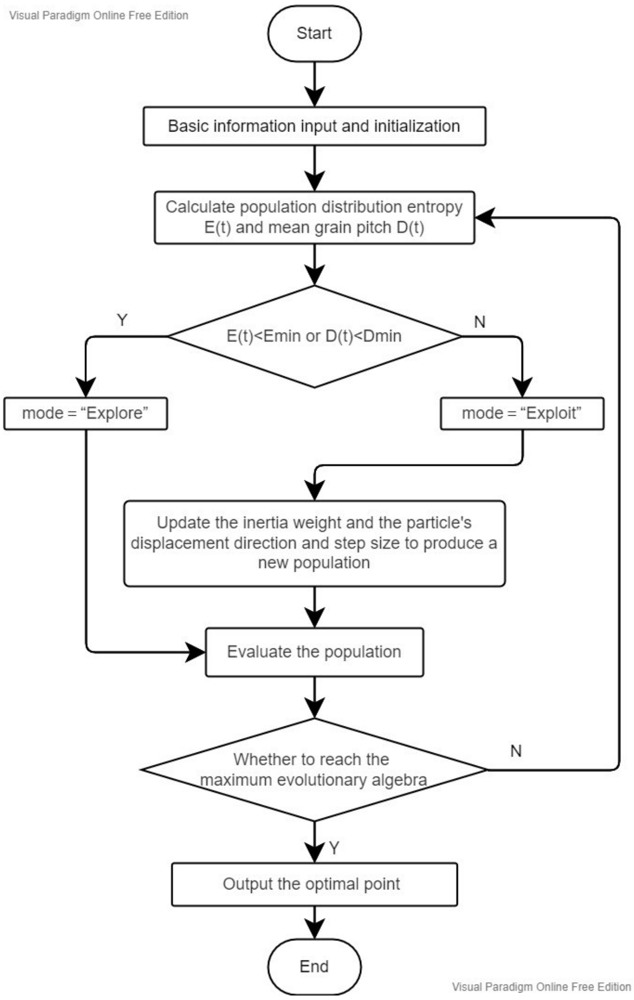

Figure 1. algorithm flow chart

ISSN: 2414-1895 DOI: 10.6919/ICJE.202206_8(6).0089

3.1 Specific Steps

Step1. Initialize, set minimum mean particle distance $D_{\min}$,maximum mean particle distance $D_{\max}$,minimum population distribution entropy $E_{\min}$,maximum population distribution entropy $E_{\max}$,variation probability p_{m},maximum evolutionary generation $T_{\max}$,precision ε,current mode mode to "Exploit". Set the current evolutionary algebra to t equal to 1,generate m particles $(x_1(t), x_2(t), \cdots, x_m(t))$ at random in the definition space R_n,forming the initial population X_t.The initial displacement $(V_1(t), V_2(t), \cdots, V_m(t))$ of each particle is randomly generated, forming the displacement matrix V_t .

Step2.Calculate the population distribution entropy E(t) and mean grain distance D(t), if E(t) is less than $E_{\min}$ or D(t) is less than $D_{\min}$, switch mode to "Explore"; if E(t) is greater than $E_{\max}$ and D(t) is greater than $D_{\max}$, switch mode to "Exploit ".

Step3.If the mode is "Exploit", go to Step4, otherwise, go to Step5 for mutation.

Step4.The inertia weight w is updated according to equation (3), and the displacement direction and step size of the particles are updated according to equations (4) and (5) to produce a new population X_t.

Step5. Evaluation of populations X_t.Firstly, we evaluate each particle's own adaptation value, i.e., compare the adaptation value of the current point of the ith particle with the adaptation value of the optimal position p_t found by the particle so far, if it is better, then update p_t, otherwise keep p_t unchanged, and then compare it with the adaptation value of the optimal position p_g found by the population so far, if it is better, then update p_g; otherwise keep p_g unchanged.

Step6.Check if the end condition is met, if so, end the search. Otherwise, make t equal to t+1 and go to Step2. The end condition is that the search reaches the maximum number of evolutionary generations $T_{\max}$, or the evaluation value is less than the given precision ε.

3.2 Algorithm Testing

Using APSO and LDW algorithms were simulated and tested with the single-peak Sphere function and the multi-peak Rastrigin function.

Although the particle swarm improvement strategy of linearly decreasing inertia weights (LDW) can significantly improve the optimization performance of particle swarm algorithms. However, the actual search process of the particle swarm algorithm is nonlinear and highly complex, and the improvement of the optimization effect is greatly limited [6][7] . Since the LDW algorithm and the APSO algorithm are similarly used in various objective optimization problems, the LDW algorithm was chosen for comparison tests.

Parameter settings: the maximum evolutionary generation of both algorithms is 1000, the number of particles is 30, the dimensionality is still set to 10-dimensional space, $w_{\max}$ and $w_{\min}$ are taken as 0.9 and 0.4, respectively, for APSO, $D_{\max}$ and $D_{\min}$ are taken as 0.25 and 0.001, $E_{\max}$ and $E_{\min}$ are taken as 2.0 and 0.25, respectively, and the variation probability p_{m} is taken as 0.005.

Table 1. Comparison of the best fits of the two algorithms

Volume 8 Issue 6, 2022
DOI: 10.6919/ICJE.202206_8(6).0089

Algorithm	LDW	APSO
Sphere	0	0
Rastrigrin	4.997	3.982

In order to analyze the whole evolutionary process more clearly, the changes of the optimal fitness values of the two functions with the number of iterations are shown in Figure 2 and Figure 3, respectively.

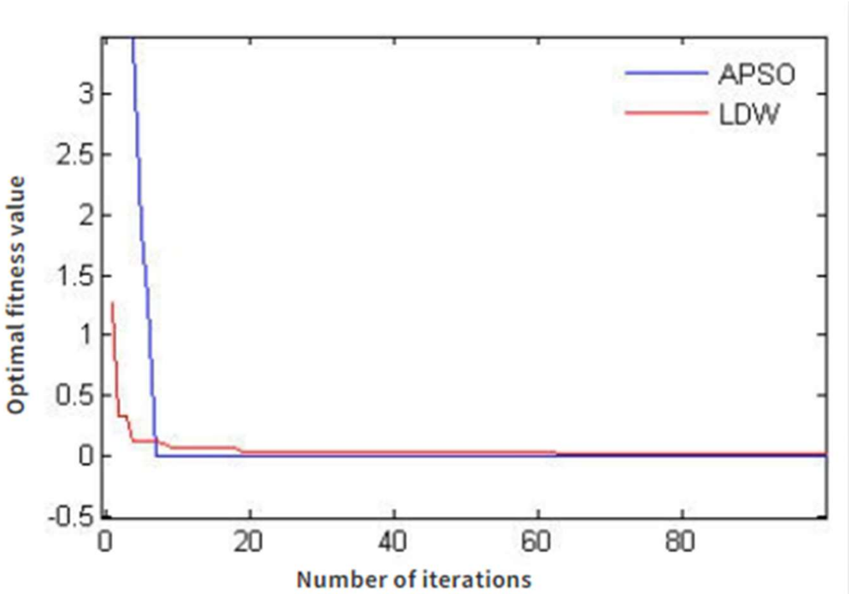

Figure 2. Comparison of function iterations for Sphere

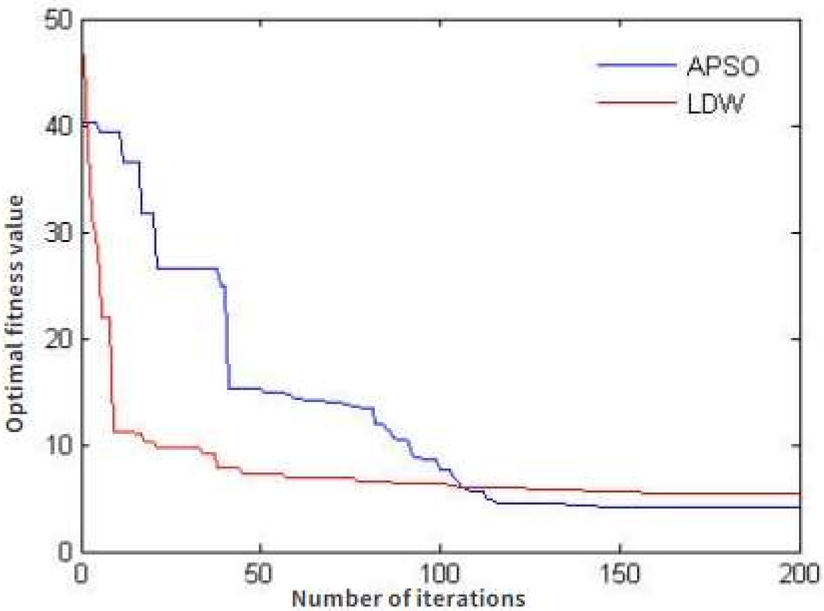

Figure 3. Comparison of function iterations of Rastrigrin

It can be seen from Table 1, Figure 2 and Figure 3 that the APSO algorithm achieves a higher degree of adaptation than the LDW algorithm for both functions tested, and the APSO algorithm improves

ISSN: 2414-1895 DOI: 10.6919/ICJE.202206_8(6).0089

less for the Sphere function, mainly because the adaptive superiority of APSO does not show for the Sphere single-peak function. The improvement is very obvious, and in the test, APSO can easily search for the optimal point, while LDW is difficult to converge to the optimal point, so APSO is more robust. From Figure 2. and Figure 3. it can be seen that there is a great improvement in the accuracy of the search for the Sphere function and the Rastrigrin function using the APSO method. The main reasons are the two strategies used: first, the alternating exploration and exploitation strategy is used to control the population diversity, so that the method can jump out of the local minima and avoid premature maturity, and thus the search accuracy is improved; second, the adaptive inertia weights are used, which makes the adjustment of global search ability and local search ability more reasonable.

In order to analyze the operation mechanism of APSO and LDW algorithms more clearly, Figure 4 and Figure 5 show the changes of the mean grain distance D(t) and the population distribution entropy E(t) with the evolutionary generation of the Sphere function and Rastrigrin function respectively.

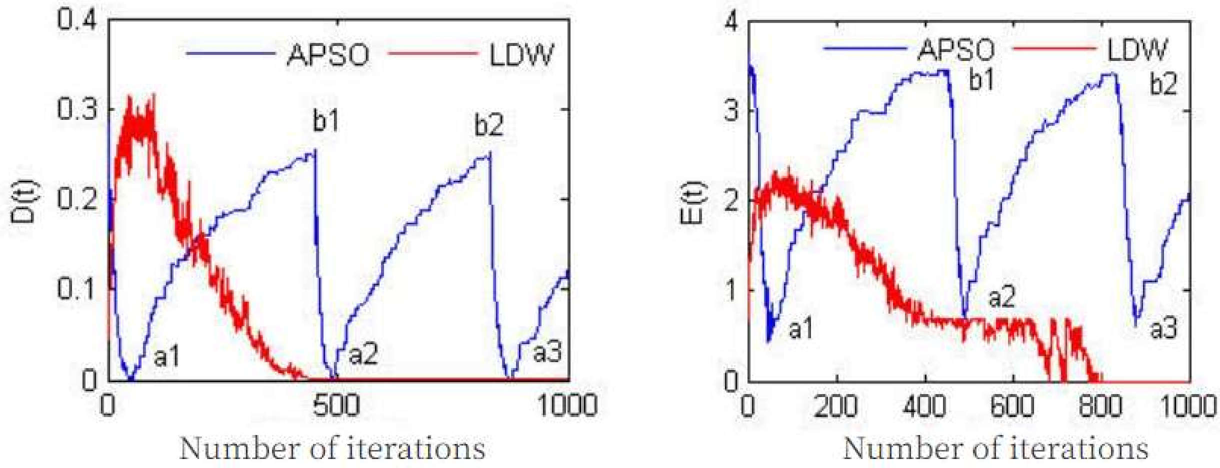

Figure 4. Comparison of the Sphere function's merit-seeking iterations

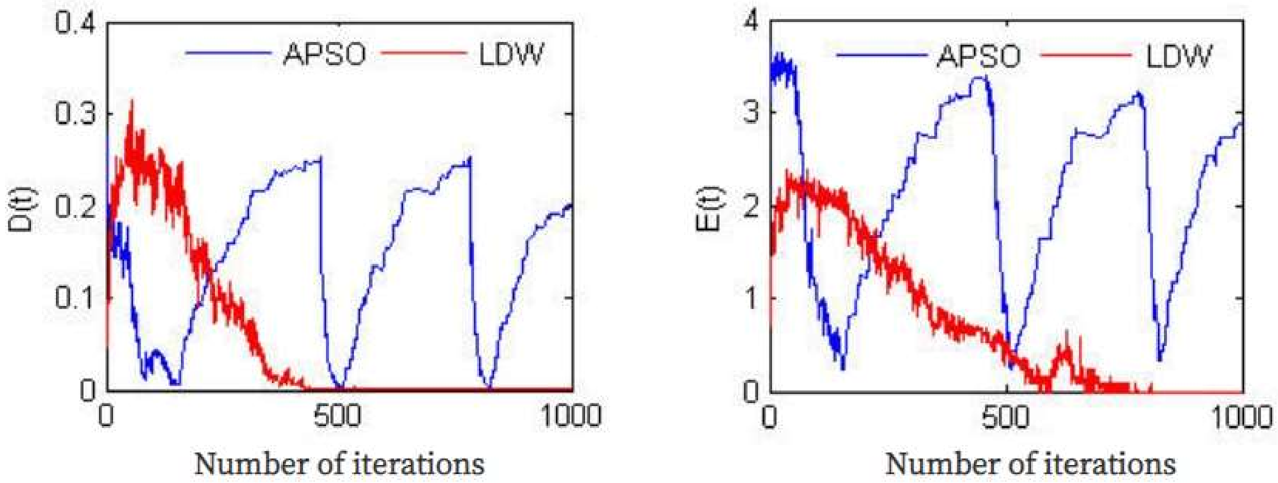

Figure 5. Comparison of the Rastrigrin function's merit-seeking iterations

From Figure 4 and Figure 5 we can see that the D(t) and E(t) of the LDW method decreases largely with the increase of evolutionary generations, which results in a rapid loss of population diversity and

ISSN: 2414-1895 DOI: 10.6919/ICJE.202206_8(6).0089

leads to a tendency to fall into local minima.For the APSO method, the variational strategy gives the particles the ability to jump out of the local minima, which further improves the accuracy of the solution.As seen in Figure 4, the population distribution entropy and the average particle distance are small when the optimization process proceeds to point a1, and the particles have a high probability of falling into local minima.At this point, the population starts to disperse using a mutation strategy until point b1, which is of the nature of the detection phase described above.When evolution reaches point b1, the population is sufficiently dispersed, the particle population starts to enter the exploitation phase, and so detection and exploitation alternate repeatedly.It can also be seen from the figure that the number of generations required for the probing phase is small and therefore the computational time required is also small.

4. Conclusion

In the same application scenario, the improvement of APSO algorithm for Sphere function is small, which is mainly for Sphere single-peak function, the adaptive superiority of APSO is not shown. For the Rastrigrin function, the improvement is very obvious, and in the test, APSO is easy to search for the optimal point, while LDW is difficult to converge to the optimal point, so APSO is robust. For the APSO method, the variational strategy gives the particles the ability to jump out of the local minima and thus has higher accuracy. The experimental results show that the adaptive particle swarm optimization algorithm has excellent performance in most cases. Therefore, the improved adaptive particle swarm optimization algorithm proposed in this paper is effective.

Acknowledgments

Natural Science Foundation. Fund: Scientific Research Project of Chengdu Technological University (No:2021zr025).

References

[1] https://baike.baidu.com/item/%E7%B2%92%E5%AD%90%E7%BE%A4%E4%BC%98%E5%8C%96/1352052?fr=aladdin.

[2] W.H. Zhu , Q.Y. Guo: Particle swarm optimization algorithm accuracy and convergence improvement and application (Industrial Control Computer, China 2015,28(4)), p.144-146. (In Chinese).

[3] C. Guo, W.D. Zhang,et al. Particle swarm algorithm for parallel collaboration of multiple swarms, Computers with Modernization 2022,(01),33-40.

[4] DE CAMPOS JR A,POZOA T R,DUARTE JR E P.Parallel multi-swarm PSO strategies for solving many objective optimization problems[J].Journal of Parallel and Distributed Computing,2019,126:13-33. J. Liu, E.L. Chen and Z.T. He: Journal of Shi Jia Zhuang Railway Institute (Natural Science), Vol. 22 (2009) No. 4, p.40-42.

[5] D.Q.Wu, J.G.Zheng Parallel Particle Swarm Optimization Algorithm Based on Hybrid Strategy Adaptive Learning. Control and Decision,2013,28(7):1087-1093.

[6] Y.X.Wu, Y.H.Liu , A Cloud Computing Task Scheduling Algorithm Based on Improved LDW Particle Swarm Optimization Algorithm(Logistics Sci-Tech No.11, 2018).

[7] Z.Zheng, K.X.Zheng, Z.L.Wu, et al. Joint Optimal Dispatching Strategy for Wind-Thermal Power System Based on Improved LDW Particle Swarm Algorithm. Guizhou Electric Power Technology, 2017, 20 (10): 50-55.