A Two Stages Invasive Weed Optimization via a New Clustering Strategy

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ABSTRACT
Invasive weed optimization (IWO), which is inspired from the invasive behavior of weeds growing in nature, has high explorative power and can converge to the optimal solution of a problem efficiently. However, the key parameter values are hard to set. Then competitive exclusion operator selects better solutions only based on fitness value, which may lead to premature convergence. In order to alleviate the two problems, this paper proposes a two stages IWO technique. In the first stage IWO mainly focuses on explorative search to find the promising solutions. With these obtained solutions picked out in the first stage, a new clustering strategy which is first proposed by this paper is adopted to capture different promising solution regions. In the second stage a modified IWO is utilized to search each promising regions carefully. Based on the results of clustering, the value of key parameter is determined by statistic information but not artificial setting. In this way parameter problem is solved and a balance between exploration and exploitation is achieved. Experimental results indicate that the proposed technique is an effective and efficient algorithm which can not only explores and exploits the promising regions in the search space effectively but also obtain the result superior to the standard invasive weed optimization.

Keywords
Invasive Weed Optimization; premature convergence; clustering strategy; two stages optimization algorithm;

1. INTRODUCTION
Intelligent optimization algorithms have some characteristic advantages over classical optimization techniques, such as simple structure, less parameters, strong robustness and easy to understand. They have reached great success in theoretical research and engineering applications so that many scholars pay attention to them. In recent years, some efficient intelligent optimization algorithms are constantly emerging, including particle swarm optimization (PSO) [1], estimation of distribution algorithm (EDA) [2], genetic algorithm (GA), differential algorithm (DE) and invasive weed optimization (IWO) [12]. Here we mainly focus on IWO.

IWO was first proposed by Mehrabian and Lucas in 2006. It simply simulates natural behavior of wild weeds in finding and colonizing suitable place for their growth and reproduction [4]. After initialization, every weed represents a solution and they reproduce new solutions which are called seeds. Spatial dispersal and competitive exclusion operators are applied to these seeds to complete the procedure [4]. Benefitted from these operators, IWO has high explorative power [4] and performs more robust, adaptive and efficient approach for solving complex problems. [4] proved that it can converge to the optimal solution of a problem efficiently. Since its inception, IWO has been successfully applied to solve various practical problems like the personalized urban multi-criteria path optimization problem [5], optimizing the spacing between the elements of the linear array [6] and optimizing no-idle flow shop scheduling problem [14].

Although IWO has many advantages, it is not free from premature convergence which is a common issue in most evolutionary computation algorithms. One reason is that competitive exclusion operator selects better solutions only based on fitness value, which may make most new weeds locate in the same solution region with their parents. Besides, IWO has different request of standard deviation (SD) value in different search stages which has great influence on algorithm performance. However, existing methods are hard to set an appropriate SD value directly. Focusing on these weaknesses, preliminary mathematical analyses on the explorative power of IWO can be found in [13]. Zhigang Ren developed an enhanced IWO (EIWO) [8]. [10] proposed the optimal foraging weed colony optimization (FWCO). Majumdar et al. [3] and Roy et al. [11] combined the neighborhood crowding technique and the group search optimizer with IWO.

In order to remedy the problems mentioned above, we propose a two stages IWO with a new clustering strategy (TS-IWO) in this paper. In the first stage IWO mainly focuses on explorative search to find high-quality solutions and it is insensitive to the value of parameters so that the value of SD is relevant large. Then a new clustering strategy is deployed to capture different promising solution regions with the obtained solutions. In the second stage, a modified IWO is utilized to search each promising regions carefully to facilitate convergence toward the global optimum. Based on the results of clustering, the value of SD is determined by statistic information but not artificial setting. In this way parameter problem is solved and a balance between exploration and exploitation is achieved.

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2. DESCRIPTION OF TS-IWO

Optimization necessitates efficient exploration of the search space at early stage and rapid convergence in the later period. For this purpose, TS-IWO is put forward which contains three main modules, as shown in Figure 1. In the first module, IWO procedure aims at explorative search to find the promising solutions so we call it explorative IWO. Here IWO is used to search promising solutions as many as possible, but not directly get optimal solutions. It is insensitive to the value of parameter so that the value of SD is relevant large. In the clustering module, a new proposed clustering strategy which comprehensively utilized the information of decision space and target space (DS-TS) is adopted to capture different promising solution regions, which not only based on distance between solutions but also fitness value. In the third module modified IWO is deployed to implement exploitative search so it is named exploitative IWO. Based on the results of clustering, the value of SD is determined by statistic information but not artificial setting. TS-IWO is based on basic IWO so that the presentation of IWO is given in the following part.

Figure 1. Three main modules of TS-IWO

2.1 Presentation of basic IWO

In contrast to traditional optimization methods, which emphasize accuracy and exact computation, IWO is a population-based meta-heuristic algorithm that mimics the colonizing behavior of weeds to adapt to external environment. The basic characteristic of a weed is that it grows its population entirely or predominantly in a geographically specified area which can be substantially large or small. At the beginning, a certain number of weeds are randomly spread over the entire space. They will eventually grow up and execute the following steps.

(1) Initialization: A finite number of weeds are initialized randomly in the feasible search area.

(2) Reproduction: The number of seeds produced by a weed is depending on its own fitness as well as the lowest and highest fitness of the population, as shown in formula (1).

$$n_{weeds} = \frac{f - f_{\min}}{f_{\max} - f_{\min}}(n_{bestpro} - n_{leastpro}) + n_{leastpro} \quad (1)$$

(3) Spatial dispersal: The distance between a seed and its parent weed obeys normal distribution with zero mean but varying standard deviation (SD) shown in formula (2).

$$\sigma_t = (\frac{t_{\max} - t}{t_{\max}})^{pow}(\sigma_{\max} - \sigma_{\min}) + \sigma_{\min} \quad (2)$$

Then, the position of the j^{th} seed produced by the i^{th} weed can be represented as formula (3).

$$S_{ij} = W_i + \sigma_t \cdot randn\left(0,1\right) \quad (3)$$

(4) Competitive exclusion: only the fittest weeds are taken in the colony and repeat step (2)-(4) until the maximum number of population size are reached.

As stated above, IWO provides a simple and clear evolutionary mechanism for optimization. Every weed grows independently so there are many centers which has powerful ability of global search. However, the spatial positions of seeds are directly decided by formula (3) while the SD value is determined by formula (2), which is influenced by other parameters. The competitive exclusion operator selects better solutions only based on fitness value, which may make most new weeds locate in the same solution region with their parents. Besides, IWO has different requirement of SD value in different search stages and it has great influence on algorithm performance. These factors usually make IWO unable to achieve the global optimum, especially for multimodal problems.

2.2 Explorative IWO

As mentioned above, explorative IWO is adopted to search promising solutions as many as possible but not directly get optimal solutions. It aims at explorative search, which mainly obeys the procedure of basic IWO. For better search effects, two improvements are put forward. First, the value of SD is set relevantly large because in the explorative stage it is insensitive to the value of parameters. Then in basic IWO competitive exclusion operator selects better solutions only based on fitness value which may make most new weeds locate in the same solution region with their parents. Therefore a more flexible select strategy that all solutions are randomly divided into different groups to choose the high-quality solutions respectively is applied here. These two points are adopted to prevent premature convergence. Since optimization requires the detection of promising solutions in early stage, IWO appears to be very suitable for this as the weeds reproduce the seeds by a very small perturbation around them. By this means, the area around weeds can be explored fully.

2.3 DS-TS clustering strategy

Here clustering algorithm is adopted to capture different promising solution regions of high-quality solutions, so we hope it has neither too many parameters nor too much calculation. [7] used IWO and k-means clustering to solve nonlinear equations system and the clustering strategy used here was influenced by argument and only relied on distance. Then in this paper a new fast clustering strategy is proposed which is inspired by the thought of [9]. The clustering strategy in [9] is based on distance and density, which is mainly used in image processing area. Considering the characteristic of objective problems, we did some improvements of the mentioned strategy to form our DS-TS clustering strategy. DS-TS chooses solutions with better fitness and farther relative distance from other solutions as cluster centers, which solves the parameter problem of existing clustering algorithms and the set of SD value.

(1) Computing the relative distance from all the solutions with better fitness

The basic distance is defined as (4).

$$\delta_{ij} = \sqrt{\left\|X_i - X_j\right\|^2 / D} \quad (4)$$

where δ_{ij} denotes the distance between i^{th} and j^{th} solution, X_i and X_j respectively represent the position of i^{th} and j^{th} solution, $\|\cdot\|$ denotes the distance and D is the dimension.

For the i^{th} weed, its distance matrix D_i contains the distance between itself and specific weeds whose fitness is better than the i^{th} weed. This can be described as (5). We predefined $D_1 = 0$.

$$D_i = \{\delta_{ij} \left| f_i > f_j, i \neq j \right.\} \tag{5}$$

After calculating the distance matrix of each weed, the minimum distance δ_i of each weed is defined as (6).

$$\begin{cases} \delta_i = \min(D_i) \\ \delta_1 = \max(\delta_i) \end{cases} (i > 1) \tag{6}$$

(2) Computing the distance threshold

The threshold of distance is shown in (7). Among the weeds with minimum distance, those who satisfy expression (8) are chosen as cluster centers. $weed(i)$ denotes the i^{th} weed.

$$\begin{cases} \delta_{\max} = \max(\delta_i) \\ \delta_{\min} = \min(\delta_i) \\ \delta_{threshold} = (\delta_{\max} - \delta_{\min}) \times 80\% \end{cases} \tag{7}$$

(3) Cluster centers and cluster members

$$centers = \{weed(i) \left| \delta_i > \delta_{threshold} \right.\} \tag{8}$$

After determining the cluster centers, the rest solutions belong to the cluster whose center has the nearest distance.

(4) Plot the relative distance as a function of fitness

To illustrate the performance of this strategy, some experiments were done and the result is shown in Figure 2. It shows the results of choosing cluster centers of unimodal function 3 with 10 dimensions. As described above, cluster centers are those points who locate in the upper area. The rest solutions are then distribute to relevant cluster. The result indicates the effectiveness of DS-TS clustering strategy.

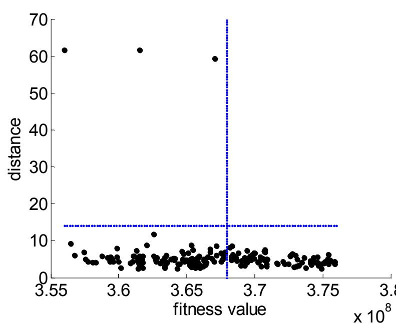

Figure 2. Result of choosing cluster centers

2.4 Exploitative IWO

In the exploitative stage, a modified IWO takes over with an efficient sub-regional search technique in each group to facilitate convergence toward the global optimum. Each cluster independently runs a separate IWO in parallel to search each promising region carefully. Within each cluster, weeds are picked out to constitute high-quality solutions according to cluster scale, which means the number of weed is calculated based on the proportion given in (9). Here we initialize the population size n and optimal solutions scale m of all generations to a fixed value.

$$m_i = \frac{n_i}{n} \cdot m \tag{9}$$

where m_i is the number of better weeds choose from the i^{th} cluster while n_i is the number of solutions in the i^{th} cluster.

A more specific operation is that weeds in different clusters and different dimensions share different SD values which are determined by statistical information of better weeds in their own clusters but not artificial setting. For i^{th} cluster the SD is determined by k better solutions in it, as shown in formula (10).

$$D_i = D(X_1, X_2, ..., X_k) \tag{10}$$

2.5 The framework of TS-IWO

The specify framework of TS-IWO is shown in Figure 3. Clustering strategy is executed every couple of iterations to adjust the distribution of clusters.

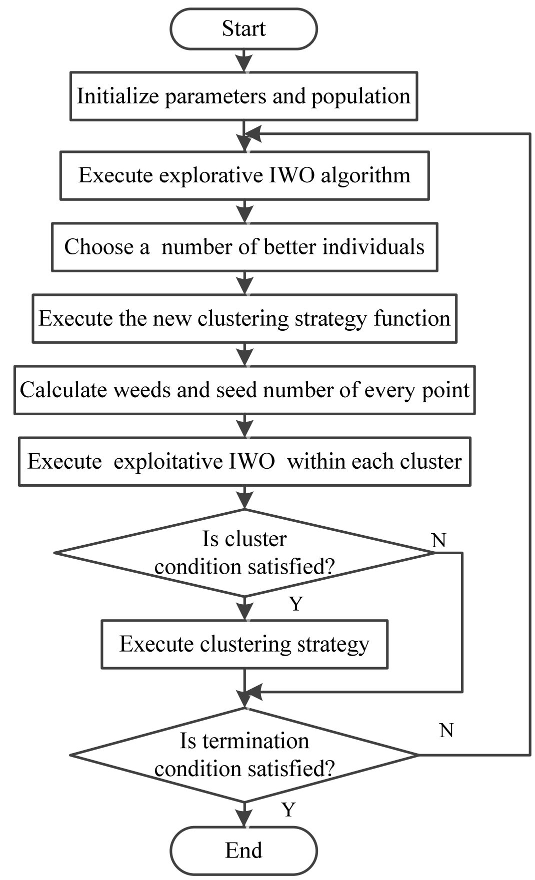

Figure 3. Framework of TS-IWO

3. EXPERIMENTAL RESULTS

3.1 Advantages over basic IWO

To verify the effectiveness and efficiency of the proposed TS-IWO, we compared it with basic IWO. The maximum number of allowable point number is set as 300,000 for dimensionality of 10.

The parameters of IWO are set to the same values as [4]: $n_{\max} = 50$, $\sigma_{\min} = 0.0001$, $\sigma_{\max} = \sqrt{(x_{\max} - x_{\min})/2}$ and $pow = 2$. The values of TS-IWO parameters are set as followed:

$n_{\max} = 5$, $n_{\min} = 1$, $\sigma_{\max} = (ub - lp)/2$, $\sigma_{\min} = (up - lp)/(2 * up * up)$. For each function, each algorithm is run for 30 different runs and the reported solution is the average taken over all the runs to reduce the accidental error. The experimental result of f_8 is shown in Figure 4 and it indicates that TS-IWO has a great advantage over basic IWO.

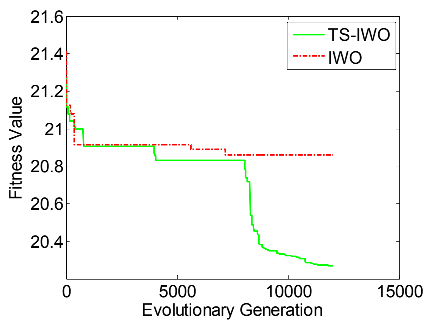

Figure 4. Result of TS-IWO and basic IWO

Compared with IWO, TS-IWO not only converges faster but also converges to a better optimum effectively. According to the results, TS-IWO performs better than basic IWO.

3.2 Comparison with other algorithms

To justify its development, results are directly compared with other three evolutionary optimizers based on the performance measures, including the basic IWO [4], Estimation of distribution algorithm (EDA) presented in [2], and a modified particle swarm optimization DMS-PSO in [1]. Its parameters are set the same values as given in 3.1. A maximum number of 3.0e+5 function evolutions were allowed in each run of the algorithm and it was tested 30 times independently on each function.

Table 1. Comparison among four algorithms

Fun	Intelligent Optimization Algorithms			
	IWO	EDA	SPSO	TS-IWO
f_1	4.67e-04	4.88e+01	**0.00e+00**	7.56e-16
f_2	3.21e-01	1.61e+02	**7.93e-09**	6.35e-05
f_3	8.10e+06	3.75e+06	6.43e+01	**3.37e+00**
f_4	9.85e+02	1.28e+03	8.51e-03	**8.84e-06**
f_5	2.31e+03	6.19e+03	3.83e+01	**1.12e+00**
f_6	4.12e+02	1.83e+05	**8.93e-08**	3.72e-01
f_7	2.98e-01	2.66e+01	5.19e-02	2.31e-01
f_8	3.19e+01	2.09e+01	2.00e+01	**1.93e+00**
f_9	8.50e+01	2.50e+02	**0.00e+00**	6.31e-04
f_{10}	3.61e+01	2.73e+02	6.22e+00	**1.97e+00**
f_{11}	1.15e+01	4.07e+01	4.89e+00	**1.25e-01**
f_{12}	8.75e+02	8.28e+05	**2.99e+00**	8.43e+01
f_{13}	1.00e+01	4.52e+03	3.97e-01	**1.36e-01**
f_{14}	3.12e+01	1.37e+01	2.34e+01	**3.67e+00**
f_{15}	2.13e+02	5.38e+02	9.85e+00	**8.85e+00**
f_{16}	4.01e+02	2.77e+02	9.50e+01	**9.98e+00**

According to the results shown in Table 1, we can draw the conclusion that the TS-IWO performances much better than other three algorithms and especially outperforms the original IWO and EDA by a large margin. In comparison with DMS-PSO, the proposed algorithm yields better solutions for 11 functions, and slightly worst for the rest functions.

The results shown above clearly indicate that the TS-IWO has outperformed all the compared algorithms in terms of the performance measures. One of the superiority of the algorithm lies in the fact that it has the capability to locate the promising solution regions, which can realize enough exploration and avoid premature convergence. The new clustering strategy which is different from previous algorithm connects decision space and target space together to implement solution space division. In the second stage the exploitative IWO takes over with an efficient sub-regional search technique in each group to facilitate convergence toward the actual optimal point. These results preliminarily verify the effectiveness and efficiency of the proposed TS-IWO.

4. CONCLUSIONS

In this paper we proposed a two stages IWO evolutionary optimization technique which is united by a new clustering strategy. This algorithm is tested for the optimization of sixteen benchmark functions. To justify its development, results are directly compared with other three evolutionary optimizers based on the performance measures. The results of our experimental study suggest that the TS-IWO not only significantly outperforms the original IWO, but also yields competitive solutions against the other three algorithms.

Based on the current results, one of the future directions is to balance the search efforts between exploration and exploitation to achieve the global optimum within limited FEs. Then, the new adaptive clustering strategy without any arguments can be applied to other intelligent optimization algorithms to recognize the spatial distribution of the objective function. These all can surely open a path leading to improved performance substantially.

5. REFERENCES

[1] De Oca, M.A.M., Stützle, T., Birattari, M. and Dorigo, M. 2009. Frankenstein's PSO: A Composite Particle Swarm Optimization Algorithm, *IEEE Transactions on Evolutionary Computation*, 13, 5(2009), 1120-1132. DOI= http://ieeexplore.ieee.org/10.1109/TEVC.2009.2021465.

[2] Dong, W., Chen, T., Peter, T. and Yao, X. 2013. Scaling up estimation of distribution algorithms for continuous optimization, *In Evolutionary Computation, IEEE Transactions on*, 17, 6(2013), 797-822. DOI= http://ieeexplore.ieee.org/10.1109/TEVC.2013.2247404.

[3] Majumdar, R., Ghosh, A., and Das, A.K. 2011. Artificial weed colonies with neighborhood crowding scheme for multimodal optimization. *In Proceeding of the International Conference on Soft Computing for Problem Solving*, 1(2011), 779-787.

[4] Mehrabian, A.R. and Lucas, C. 2006. A novel numerical optimization algorithm inspired from weed colonization. *Ecological Informatics*, 1, 4(2006), 355-366. DOI= http://ieeexplore.ieee.org/ 10.1109/CCDC.2013.6561800.

[5] Pahlavani, P., Delavar, M.R., Frank, A.U. 2012. Using a modified invasive weed optimization algorithm for a personalized urban multi-criteria path optimization problem. *International Journal of Applied Earth Observation & Geoinformation*, 18, 1(2012), 313-328.

[6] Pal, S., Basak, A., Das, S. and Abraham, A. 2009. Linear Antenna Array Synthesis with Invasive Weed Optimization Algorithm. *In Soft Computing and Pattern Recognition, SOCPAR '09, International Conference of*, (2009), 161-166. DOI= http://ieeexplore.ieee.org/ 10.1109/SoCPaR.2009.42.

[7] Pourjafari, E. and Mojallali, H. 2012. Solving nonlinear equations systems with a new approach based on invasive weed optimization algorithm and clustering, *Electrical engineering department*, 4(2012), 33-43. DOI= http://ieeexplore.ieee.org/10.1109/POWERCON.2010.5666389.

[8] Zhigang, R., Wen, C., Aimin, Z. and Chao, Z. 2013. Enhancing invasive weed optimization with taboo strategy, *GECCO'13 Companion* (Amsterdam, Netherlands, 2013), 1659-1662. DOI= 10.1145/2464576.2466815.

[9] Rodriguez, A. and Laio, A. 2014. Machine learning. Clustering by fast search and find of density peaks. *Science*, New York, N.Y., 2014. 344, 6191, 1492-1496.

[10] Roy, G.G., Chakroborty, P., Zhao, S., Das, S. and Sugantha, P.N. 2010. Artificial foraging weeds for global numerical optimization over continuous spaces. *In Proc. IEEE Congr. Evol. Comput.*, 1-8(2014), Barcelona, Spain. DOI= http://ieeexplore.ieee.org/ 10.1109/CEC.2010.5585917.

[11] Roy, S., Islam, S.M., Das, S. and Ghosh, S. 2013. Multimodal optimization by artificial weed colonies enhanced with localized group search optimizers, *Applied Soft Computing*, 13, 1, 27—46. DOI= http://www.softcomputing.org/10.1016/j.asoc.2012.08.038.

[12] Xuncai, Z., Guangzhao, C., and Yanfeng, W. 2010. A modified invasive weed optimization with crossover operation. *In Intelligent Control and Automation* (WCICA), 2010 8th World Congress, 11-14.

[13] Xuncai, Z., Jin, X., Guangzhao, C., Yanfeng, W and Ying N. 2008. Research on invasive weed optimization based on the cultural framework. *In 3rd International Conference on Bio-Inspired Computing: Theories and Applications*, 7, 5, 129-134.

[14] Zhou Y., Chen H. and Zhou G. 2014. Invasive weed optimization algorithm for optimization no-idle flow shop scheduling problem. *Neurocomputing*, 137, 285-292. DOI= 10.1016/j.neucom.2013.05.063.