Enhancing Invasive Weed Optimization with Taboo Strategy

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ABSTRACT
Invasive weed optimization (IWO) is a recently developed metaheuristic that imitates the invasive behavior of weeds in nature. However, the reproduction and spatial dispersal operators in original IWO may make most seeds located around the best weed, which will result in premature convergence. To overcome this drawback, we propose an enhanced IWO algorithm (EIWO) by utilizing the core idea of taboo search. When no better solution is found in the neighborhood of a weed within a certain number of iterations, EIWO judges that this weed has been stagnated and taboos it, thus avoiding the repeated search in its neighborhood. In addition, EIWO also defines a self-production operator which generates some new weeds in a random way rather than directly choosing from the current plant population, so that new solution regions can be explored. To verify the efficiency of the proposed algorithm, we compared it with the original IWO, an improved IWO, and a modified particle swarm optimization on a set of 16 benchmark functions. Computational results indicate that EIWO can prevent premature convergence and produce competitive solutions.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *heuristic methods*

General Terms
Algorithms

Keywords
Invasive Weed Optimization, Metaheuristic, Premature Convergence, Taboo Search

1. INTRODUCTION
Optimization problems are ubiquitous in scientific research and engineering practice. People have been seeking for efficient methods to tackle them. The derivative requirement and computation burden of most mathematical programming methods force researchers to pay attention to nature-inspipred metaheuristics. Under this background, Mehrabian and Lucas proposed invasive weed optimization (IWO) in 2006 by mimicking the ecological behavior of weeds in colonizing and finding suitable place for growth and reproduction [2]. IWO shares many features with other evolutionary computation methods, but does not use evolution operators such as crossover and mutation. Instead, it employs some distinctive operators, including reproduction, spatial dispersal, and competitive exclusion.

Since its inception, IWO has attracted many research efforts, and some interesting variants have been developed. Roy *et al.* [5] incorporated the optimal foraging theory into IWO and proposed a variant named foraging weed colony optimization (FWCO). Zhang *et al.* [14] developed a cultural IWO by embedding IWO into the framework of the cultural algorithm. Basak *et al.* [1] developed a differential IWO by introducing some features of differential evolution into IWO. Majumdar *et al.* [11] and Roy *et al.* [13] combined the neighborhood crowding technique and the group search optimizer with IWO, respectively, with the aim of improving its performance in solving multimodal problems. Preliminary mathematical analyses on the explorative power of IWO can be found in [8]. In the aspect of application, IWO has been successfully used to solve various practical problems like tuning of a robust controller [2], developing a recommender system [7], antenna configuration optimization [3], encoding sequences for DNA computing [15], and design of aperiodic thinned array antennas [12].

However, IWO is not free from premature convergence which is a common issue in most evolutionary computation algorithms. By giving better weeds more chances to survive and allowing them to produce more seeds, IWO puts more and more search efforts around the best solution found so far and gradually loses exploration ability, thus resulting in premature convergence. Focusing on this disadvantage, we propose an enhanced IWO algorithm (EIWO) which incorporates the core idea of taboo search (TS) while following the basic framework of the original IWO. TS, proposed by Glover [4], was incipiently used to solve combinatorial optimization problems. It enlarges search regions and prevents premature convergence by forbidding certain classified moves. Chelouah *et al.* [10] expanded the idea of TS into continuous domain and verified its efficiency. To the best of our knowledge, no study has been done on integrating TS into IWO. In EIWO, TS is employed to taboo those fully exploited weeds even if they are of high fitness, for the purpose of avoiding meaningless repeated search. To ensure its exploration ability, EIWO also defines a self-production operator which generates a part of new weeds in a random way rather than chooses from the current plant population, so that new solution regions can be detected. The above revisions on IWO are easy to implement and show significant performance improvements according to the experimental results.

The rest of this paper is organized as follows. Section 2 simply introduces the basic idea of IWO. Section 3 presents the proposed EIWO in detail. Section 4 describes experimental settings and analyzes experimental results. Finally, conclusions are drawn in section 5.

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2. ORIGINAL IWO

Weeds change their behavior to adapt with external environment during the colonizing process, and show strong invasiveness and vitality. IWO is a population-based metaheuristic that imitates the invasive behavior of weeds. The main steps of the original IWO can be summarized as follows:

1) Initialization*:* A finite number of weeds are dispread over the solution space in a random way. The position of each weed represents a solution.

2) Reproduction*:* Each weed is allowed to produce seeds depending on its own fitness as well as the lowest and highest fitness of the population, such that the number of seeds produced by a weed increases linearly from a minimum value for the worst weed to a maximum value for the best weed.

3) Spatial dispersal*:* The seeds produced by a weed are located within a specified region centered at the position of this weed, which leads to a local search around the weed. The distance between a seed and its parent weed obeys normal distribution with zero mean but varying standard deviation (SD). The SD is made decrease over the generations. If $\sigma_{\max}$ and $\sigma_{\min}$ represent the maximum and minimum SD, respectively, the SD in a particular generation (or iteration) *t* is given by

$$\sigma_t = \left(\frac{t_{\max} - t}{t_{\max}}\right)^{pow}(\sigma_{\max} - \sigma_{\min}) + \sigma_{\min} \tag{1}$$

where $t_{\max}$ is the maximum number of iterations allowed, and pow is a nonlinear modulation index. The position of a seed *j* produced by weed *i* can be formulated as

$$S_{ij} = W_i + \sigma_t \cdot \mathrm{randn}(0,1) \tag{2}$$

where randn(0, 1) returns a random number obeying the standard normal distribution.

4) Competitive exclusion*:* To limit the maximum number of plants in the population, it is necessary to introduce competition among plants. Initially, all the weeds are allowed to reproduce, and all the produced seeds are included in the population until the number of plants reaches a maximum value $n_{\max}$. By this time, it is expected that only the fittest plants survive and reproduce. Concretely, IWO first ranks the weeds and offspring together according to their fitness, and then picks out $n_{\max}$ fittest plants to implement steps *1) – 4)* and discards other plants. This process continues until a predefined maximum number of iterations or function evaluations are reached.

As described above, IWO provides a simple and clear evolutionary mechanism for search. On the one hand, it distributes seeds in far distance from their parent weeds in early iterations by assigning a high value to SD, with the aim of exploring more solution regions. On the other hand, IWO gradually decreases SD in order to spread the seeds in vicinity of their parent weeds, thus concentrating the search around good solutions.

However, there are two drawbacks in the original IWO. Through some simple experiments and statistical analysis, it is easy to find that the seeds produced by some high-quality weeds are often of greater fitness than other weeds. According to the competitive exclusion operator, those relatively low-quality weeds will be replaced by these new seeds which are located in the same solution regions with their parents. This will cause that some solution regions are needlessly over-explored and the others cannot be fully explored. Besides, the performance of IWO depends on the initial positions of weeds. During the evolutionary process, seeds scatter around their parent weeds and no substantive movement takes place [8]. As a result, some solution regions might remain unexplored. These two drawbacks usually lead IWO to premature convergence and make it unable to achieve the global optimum, especially for multimodal problems.

3. ENHANCED IWO

EIWO tries to prevent over-exploring a solution region by integrating with a TS strategy and to keep its exploration ability by introducing a self-production operator. This section first describes these two new algorithmic schemes, and then presents the framework of EIWO.

3.1 Taboo Search Strategy in EIWO

In each iteration of EIWO, we do not immediately carry out the competitive exclusion operator after the spatial dispersal operation, but first check whether each weed is improved by its seeds. If a weed is not improved within g_1 ($g_1 > 0$) successive iterations, we consider it stagnated and put it into a taboo list. The plants that lie in the neighborhoods of these tabooed weeds and are of lower fitness will be eliminated from the current population.

Let $\boldsymbol{W}$ be the set of current weeds, $\boldsymbol{S}_i$ the set of seeds produced by a weed $W_i \in \boldsymbol{W}$ in current iteration, and $\boldsymbol{TL}$ the taboo list. Then the current plant population can be represented as

$$\boldsymbol{P} = \boldsymbol{W} \cup \boldsymbol{S}_1 \cup \boldsymbol{S}_2 \cup \cdots \cup \boldsymbol{S}_{|\boldsymbol{W}|}. \tag{3}$$

The plants needing to be eliminated by a tabooed solution $T_i \in \boldsymbol{TL}$ can be represented as

$$\boldsymbol{E}_i = \{P_j \in \boldsymbol{P} \mid \Delta(P_j, T_i) \le \delta_i; F(P_j) < F(T_i)\} \tag{4}$$

where $\Delta(\cdot,\cdot)$ denotes the distance between two solutions, δ_i is a positive parameter that decides the size of the tabooed region by the solution T_i , and $F(\cdot)$ denotes the fitness function. The purpose of adding the fitness condition in (4) is to avoid deleting those promising solutions.

Since EIWO mainly focuses on continuous problems, $\Delta(\cdot,\cdot)$ can be defined as the Euclidean distance. The parameter δ_i has significant influence on the performance of EIWO. The greater δ_i is, the more plants will be deleted by T_i . It is difficult to select a proper fixed value for different δ_i to adapt with all kinds of problems. A feasible way is to choose a value for each δ_i according to the real size of the solution region explored by EIWO around the corresponding weed. That is, if a weed $W_i \in \boldsymbol{W}$ is judged to be tabooed (without loss of generality, assume it corresponds to $T_i \in \boldsymbol{TL}$), δ_i is set to

$$\delta_i = \max\{\Delta(S_{ij}, W_i) \mid \forall S_{ij} \in \boldsymbol{S}_i\}. \tag{5}$$

After the elimination operation on plant population $\boldsymbol{P}$, the remaining plants $\boldsymbol{P}' \in \boldsymbol{P} \setminus (\boldsymbol{E}_1 \cup \boldsymbol{E}_2 \cup \cdots \cup \boldsymbol{E}_{|\boldsymbol{TL}|})$ are sent to the competitive exclusion operator.

TS strategy provides an efficient method to prevent repeated search. However, it is entirely possible that the tabooed regions may contain some promising solutions. In this sense, it is worthy to introduce an *aspiration criterion* for tabooed solutions. EIWO implement this in an implicit way. It sets ***TL*** with a fixed length *tl* (*tl* > 0) and releases the tabooed solutions in a first-in-first-out fashion. Once a solution is released, its neighborhood is allowed to explore again and some better solutions may be found. On the contrary, if no tabooed solution is released, it means that EIWO can always find better solutions in the neighborhoods of the current weeds. Furthermore, the introduction of this *aspiration criterion* avoids the infinite increase of ***TL***, thus saving much computational cost.

Since EIWO tends to do local search around the existing weeds, few seed will be located in the neighborhoods of the tabooed weeds, and then it is unnecessary to carry out the elimination operation with a tabooed weed in every iteration. A simple and practical way is to perform it occasionally in every g_2 ($g_2 > 0$) iterations, which further contributes to reducing computational cost.

3.2 Self-production Operator

To enable EIWO to explore new solution regions, a self-production operator is defined. It generates a part of new weeds in a random way rather than directly choosing from the current plant population so as to provide a certain chance to explore possibly undetected solution regions. However, if this operation is completely random, the generated weeds may be eliminated in the next iteration by the competitive exclusion operator, which will deteriorate the performance of the algorithm. Hence, the randomly generated weeds are further moved towards the best weed found so far, with the motive of forcing them towards a promising solution region. The above process can be mathematically described as

$$W_{\text{new}}^0 = X_{\min} + \text{rand}(0,1) \cdot (X_{\max} - X_{\min}), \tag{6}$$

$$W_{\text{new}} = W_{\text{new}}^0 + \text{rand}(0,1) \cdot (W_{\text{gb}} - W_{\text{new}}^0) \tag{7}$$

where $X_{\max}$ and $X_{\min}$ are the upper bound and lower bound on the variables being optimized, respectively, W_{gb} is the best weed found so far, and rand(0, 1) returns a random number uniformly distributed in the interval (0, 1).

Since EIWO is of strong exploration ability at the early search stage and is expected to do fine local search at the late stage, it is necessary to vary the number of weeds generated by the self-production operator in different iterations. Based on this consideration, this number is changed as follows:

$$n_{\text{sp}} = \lfloor (1 - 4(t / t_{\max} - 0.5)^2) n_{\max} \times 20\% \rfloor \tag{8}$$

where the notation $\lfloor \cdot \rfloor$ denotes the round down operation. According to (8), n_{sp} increases nonlinearly from zero until the intermediate stage of the search when it gets the maximum value, $\lfloor 0.2 n_{\max} \rfloor$. After that, n_{sp} gradually reduces to zero.

In each iteration, EIWO gets the other $n_{\max} - n_{\text{sp}}$ weeds from the plant set $\boldsymbol{P}'$ by performing the competitive exclusion operator on it. The framework of EIWO is given in Figure 1.

4. EXPERIMENTAL STUDY

We evaluated EIWO by comparing it with three other algorithms, including the original IWO [2], an improved IWO, FWCO, presented in [5], and a modified particle swarm optimization, DMS-PSO, presented in [6]. A total of 16 benchmark functions from [9] were employed in our experiment, where the first 5 are unimodal functions and the other 11 are multimodal ones. The dimensions of all these functions were set to 30.

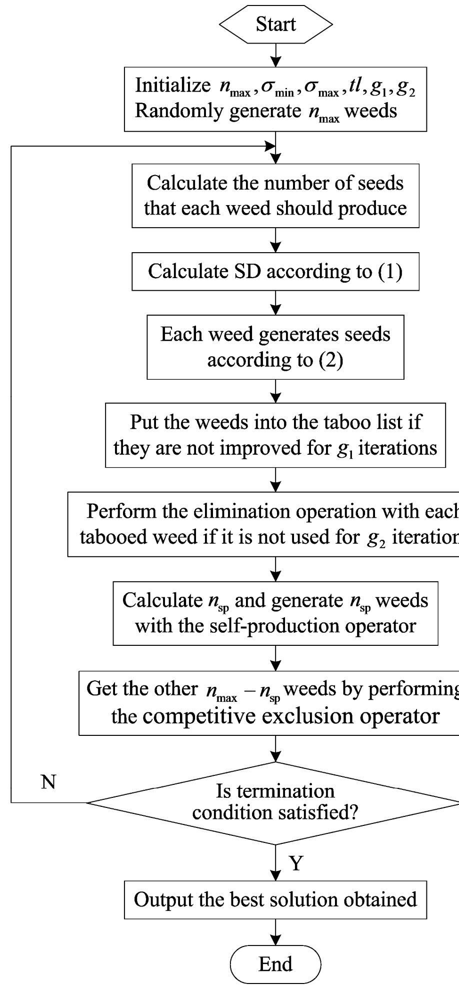

Figure 1. Framework of EIWO

Since this is only a preliminary study, its main objective is to investigate the relative strength and weakness of the new proposed algorithmic schemes, and not to show that EIWO may outperform many other optimizers. Therefore its parameters were not delicately tuned. $n_{\max}$, $\sigma_{\min}$, $\sigma_{\max}$, and *pow* were set to the same values as those in FWCO, i.e., $n_{\max} = 50$, $\sigma_{\min} = 0.0001$, $\sigma_{\max} = \sqrt{(x_{\max} - x_{\min}) / 2}$, and $pow = 2$. The values of the three new parameters were set by simple trial and error. They were $tl = \lfloor n_{\max} / 5 \rfloor$, $g_1 = 5$, and $g_2 = 10$. A maximum number of 3.0e+5 function evaluations were allowed in each run of an algorithm, and each algorithm was tested 25 times independently on each function. Table 1 reports the mean errors between the final objective function values and the corresponding real optimal values, where the results of IWO, FWCO, and DMS-PSO are obtained from [5] and the best results are marked in boldface.

According to the results listed Table 1, it appears that there is no algorithm performing best on all of the test functions. EIWO improves the original IWO by a large margin, outperforms FWCO on 13 out of total 16 functions, and generates the same solutions with FWCO for function f_1. In comparison with DMS-PSO, EIWO yields better solutions for 12 functions, the same solutions for functions f_1 and f_9, where they both obtain the optima in each run, and slightly worse solutions for functions f_6 and f_{15}. These results preliminarily verify the effectiveness and efficiency of the proposed TS strategy and self-production operator.

Table 1. Solution quality comparison among four algorithms

Function Name	IWO	FWCO	DMS-PSO	EIWO
f_1: *S*-Sphere	4.67e-04	**0.00e+00**	**0.00e+00**	**0.00e+00**
f_2: *S*-Schwefel's 1.2	3.21e-01	3.12e-09	7.93e-09	**1.25e-09**
f_3: *S*-*R*-Elliptic	8.10e+06	2.72e+02	6.43e+01	**3.79e-05**
f_4: *S*-*N*-Schwefel's 1.2	9.85e+02	**0.00e+00**	8.51e-03	7.92e-09
f_5: *B*-Schwefel's 2.6	2.31e+03	7.40e+00	3.83e+01	**4.86e-03**
f_6: *S*-Rosenbrock	4.12e+02	9.77e-01	**8.93e-08**	3.27e-05
f_7: *S*-*R*-Griewank	2.98e-01	1.12e-02	5.19e-02	**9.59e-06**
f_8: *S*-*R*-Ackley	3.19e+01	2.00e+01	2.00e+01	**7.63e+00**
f_9: *S*-Rastrigin	8.50e+01	1.90e-01	**0.00e+00**	**0.00e+00**
f_{10}: *S*-*R*-Rastrigin	3.61e+01	2.00e-01	6.22e+00	**5.04e-03**
f_{11}: *S*-*R*-Weierstrass	1.15e+01	4.92e-01	4.89e+00	**2.72e-02**
f_{12}: Schwefel's 2.13	8.75e+02	**3.00e-02**	2.99e+00	2.06e+00
f_{13}: Griewank+Rosenbrock	1.00e+01	1.98e-02	3.97e-01	**6.41e-04**
f_{14}: *S*-*R*-Scaffer's F6	3.12e+01	2.03e+00	2.34e+01	**3.69e-01**
f_{15}: Hybrid Composition	2.13e+02	2.89e+01	**9.85e+00**	1.35e+01
f_{16}: Rotated Hybrid Composition	4.01e+02	9.09e+01	9.50e+01	**2.15+01**

* '*S*-' indicates that the optimization variables are *shifted*.
'*R*-' indicates that the optimization variables are *rotated*.
'*N*-' indicates that the function contains *noise*.
'*B*-' indicates that the optimal solution is located on *bound*.

5. CONCLUSIONS

A novel IWO variant named EIWO is presented in this paper. It inherits the basic idea of IWO, and introduces two new algorithmic schemes aiming at the weakness of the original IWO. Equipped with the proposed taboo strategy, EIWO can be prevented from over-exploring a solution region. The new defined self-production operator enables EIWO to always keep a certain exploration ability. As a result, premature convergence can be avoided to a great extent. Experimental results on 16 well-known benchmark functions indicate that EIWO not only significantly outperforms the original IWO, but also yields competitive solutions against the other two algorithms tested.

This is only a preliminary study. Future work will focus on investigating the influences of each parameter and each algorithmic scheme on the performance of EIWO, and testing it on more complicated problems.

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