Improved Invasive Weed Optimization Based on Hybrid Genetic Algorithm

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Abstract

An improved Invasive weed optimization (IWO) based on hybrid genetic (HGIWO) is presented. In the new arithmetic, the inertial weight is adaptively adjusted to improve the convergence speed. The weeds are multiples by the selection and hybridization of genetic arithmetic. The import of hybrid genes improves excellent performance of weeds and reduces likelihood on getting into local optimization. The performance of the proposed method is evaluated by a number of test functions. Computational results reveal that the algorithm can be efficiently applied to the function optimization.

Keywords: Invasive Weed Optimization; Hybrid Genetic Algorithm; Evolutionary Computation

1 Introduction

Invasive Weed Optimization (IWO) is a continuous, stochastic numerical algorithm inspired from weed colonization which is proposed by Mehrabian and Lucas in [1]. IWO has shown successful results in many practical applications like optimization and tuning of a robust controller [1], developing a recommender system [2], design of encoding sequences for DNA computing [3], distributed identification and adaptive control of a surge tank [4], analysis of electricity markets dynamics [5], optimal positioning of piezoelectric actuators [6], and adaptive beam forming [7].

Despite its recent development, it has shown successful results in a number of practical applications. However, it was pointed out that IWO usually suffers from premature convergence, tuning to get stuck in local optima, low solution precision and so on. In order to overcome such a drawback, the paper proposes a modified IWO algorithm, which combines the conventional IWO technique with the Hybrid Genetic Algorithm. The Hybrid Genetic Algorithm, which is a population-based search and optimization method that mimics the process of natural evolution. The two main concepts of natural evolution, which are natural selection and genetic dynamics, inspired the development of this method. The basic principles of this technique are first laid down...
by Holland and are well described. Here, it is adopted to increase the exploration and exploitation capability of the IWO mechanism while not preventing the inherent evolution process of the conventional IWO. The numerical studies have shown the superiority of the suggested approach (HGIWO) to the existing studies as well as the traditional IWO method. The robustness of the proposed approach will be tested against a set of benchmark test functions and the results are compared extensively with those obtained by the IWO and PSO.

The organization of this paper is as follows. In section II, the original IWO model and our proposed modifications to IWO are described while in Section III, we go through some numerical test results and discussions are presented. Finally, conclusions are drawn and future works are presented in Section IV.

2 Invasive Weed Optimization Based on Hybrid Genetic Algorithm

Due to IWO's distinctive properties, its global and local abilities for exploration and exploitation, and also its successful results in a considerable number of applications after a short time of its development, we are motivated to introduce HGIWO. The main framework is as same as IWO's, while some considerations are taken for exploration in discrete search space. At first, we explain IWO briefly, and then explored it to Hybrid Genetic based version.

2.1 Overview of IWO

Invasive Weed Optimization (IWO) is a meta-heuristic algorithm that mimics the colonizing behavior of weeds. 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. There are four steps of the algorithm as described below:

1) Initialization a population: A certain number of weeds are randomly spread over the entire search space (D-dimensional). This initial population of each generation will be termed as \( X = \{x_1, x_2, \ldots, x_m\} \).

2) Reproduction: Each member of the population \( X \) is allowed to produce seeds within a specified region centered at its own position. The number of seeds produced by \( x_i \), \( i \in \{1, 2, \ldots, m\} \), depends on its relative fitness in the population with respect to the best and worst fitness. The number of seeds produced any weed varies linearly from \( \text{min}_\text{seed} \) to \( \text{max}_\text{seed} \) with \( \text{min}_\text{seed} \) for the worst member and \( \text{max}_\text{seed} \) for the best member in the population.

3) Spatial Dispersal: The generated seeds are being randomly distributed over the d-dimensional search space by normally distributed random numbers with zero mean and variance \( \sigma^2 \). However, the standard deviation \( \sigma \) is made to decrease over the generations in the following manner. If \( \sigma_{\text{max}} \) and \( \sigma_{\text{min}} \) are the maximum and minimum standard deviation, then the standard deviation in particular generation (or iteration) is given by, where \( nmi \) represents the non-linear modulation index. This step ensures that the probability of dropping a seed in a distant area decreases non-linearly so that the algorithm gradually moves from exploration to exploitation with
increasing generations.

\[ \sigma_{\text{iter}} = \sigma_{\text{min}} + \left( \frac{\text{iter}_{\text{max}} - \text{iter}}{\text{iter}_{\text{max}}} \right)^{nmi} (\sigma_{\text{max}} - \sigma_{\text{min}}) \]  

4) Competitive Exclusion: If a plant leaves no offspring then it would go extinct, otherwise they would take over the world. Thus, there is a need of some kind of competition between plants to limit the maximum number of plants in a population. Initially, the plants in a colony will reproduce fast and all the produced weeds will be included in the colony, until the number of plants reaches a maximum value of \( \text{pop}_{\text{max}} \). From then on, only the fittest plants, among the existing ones and the reproduced ones; are taken in the colony and the steps 1 to 4 are repeated until the maximum number of iterations (or function evaluations) have been reached. So, in every generation the population size must be less than or equal to \( \text{pop}_{\text{max}} \). This method is known as competitive exclusion and is a selection procedure of IWO.

2.2 Improved IWO based on hybrid genetic (HGIWO)

In nature, evolution is mostly determined by natural selection, where individuals that are better are more likely to survive and propagate their genetic material. The encoding of genetic information is done in a way that admits asexual reproduction which results in offspring’s that are genetically identical to the parent. The improved of IWO based on hybrid genetic algorithm refers combination of crossover and mutation thought of genetic algorithm, by the use of the cross factor arises out of solution set on behalf of new species. This process will lead to the population natural evolution as the same later than the previous generation population more adapt to the environment, thus the search to the global optimal solution.

In cross factor method, select half particles whose fitness value are higher directly go into the next generation, at the same time use the fitness good first half the particle’s position and speed vector replace fitness the lower half of the particles, and keep the latter vector corresponding individual extreme unchanged. In cross mechanism, h Half after particles As to cross factor random combination pairing, the same crossover operation produce offspring as genetic algorithm, and generate offspring, and compare with father generation, half particle which fitness value is better go into the next generation. Thus, through the cross can increase the diversity of particles jumping out of the local optimum, at the same time, can increase convergence speed.

In conclusion, this paper proposed an improved IWO algorithm, it is described as below:

1. Generate random plants of \( N_0 \) individuals from the set of feasible solutions
2. \( i := 1 \)
3. do
   a. Compute maximum and minimum fitness in the colony
   b. For each individual \( w \in W \)
      i. Compute the number of seeds for \( w \), corresponding to its fitness
      ii. Randomly select the seeds from the feasible solutions around the parent plant \( (w) \) in a neighborhood with normal distribution, the seed number is determined as Fig 1.
      iii. Add the generated seeds to the solution set, \( W \).
iv. For that parent plant whose seeds number is limited to zero, select corresponding number of generated seeds to do hybrid operation.

\[ \text{Seed}(x) = P \times \text{Parent}(x) + (1.0 - p) \times \text{Parent}(x) \]  
\[ P \text{ is random value between 0 and 1.} \]

Add the generated seeds to the solution set, again.

c. If total number exceeds \( p_{\text{max}} \)
   i. Sort the population \( N \) in descending order of their fitness
   ii. Truncate population of weeds with smaller fitness until \( N = P_{\text{max}} \)
d. \( i = i + 1 \)

4. Repeat 3 until the maximum number of iterations

3 Experimental Evaluations of HGIWO

The performance of the proposed HGWO is compared with the IWO on widely used benchmark test functions for continuous function optimization. First, we defined standard functions. The functions introduced are often used as quantitative evaluation means for the benchmark tests of GA and other techniques. Next, the mean solution or success ratio is presented to evaluate the proposed HGWO, and IWO.

3.1 Test functions and brief introduction

\textbf{F1: Sphere Function} \( \min f(x) = \sum_{i=1}^{n} x_i^2 \)

\textbf{F2: Rastrigin Function} \( \min f(x) = \sum_{i=1}^{n} (x_i^2 - 10 \cos(2\pi x_i) + 10) \quad \forall x_i \in [-10, 10] \)

\textbf{F3: Rosenbrock Function} \( \min f(x) = \sum_{i=1}^{n-1} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2) \)

\textbf{F4: Griewank function} \( \min f(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{n}}) + 1 \)

Sphere Function is a continuous, strongly convex function. It serves as a test case for convergence speed. The value of each of the \( N \) variables is constrained to a range of -100 to 100. It is known that the optimal value of the function is zero when all \( N \) variables are equal to zero. This Rosenbrock function has one minimum \( f_{\text{min}} = 0 \), for \( x_i = 1, i = 1, ..., N \), where \( x_i \in (-10, 10) \). It is implemented generalized multi-dimensional variant of this function. The minimum is located on the top of flat hill and it is difficult to be differentiated among very similar neighbor locations. It needs precise local search. Some optimization methods cannot achieve this minimum. Therefore this test problem can be a good criterion for robustness.

3.2 Experimental results and analysis

For the purpose of comparison between the HGWO and IWO algorithms, all the experiments used the same basic parameter settings; they are shown in table 1. To facilitate the experimentation, we use the Matlab to do simulation.
The performance of the proposed algorithm is specified in two criteria, the percentage of success, as represented by the number of trials required for the object function to reach its known target values, for example, we define 0.005 for those target values is 0.

The average value of the solution obtained in all trails.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Quantity</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_0$</td>
<td>Number of initial population</td>
<td>10</td>
</tr>
<tr>
<td>$it_{max}$</td>
<td>Maximum number of iterations</td>
<td>500</td>
</tr>
<tr>
<td>$P_{max}$</td>
<td>Maximum number of plants</td>
<td>30</td>
</tr>
<tr>
<td>$S_{max}$</td>
<td>Maximum number of seeds</td>
<td>3</td>
</tr>
<tr>
<td>$S_{min}$</td>
<td>Minimum number of seeds</td>
<td>0</td>
</tr>
<tr>
<td>$n$</td>
<td>Nonlinear modulation index</td>
<td>3</td>
</tr>
<tr>
<td>$\sigma_{initial}$</td>
<td>Initial value of standard deviation</td>
<td>5,10</td>
</tr>
<tr>
<td>$\sigma_{final}$</td>
<td>Final value of standard deviation</td>
<td>1e-2,1e-5</td>
</tr>
</tbody>
</table>

Table 1: IWO parameter values

The performance of the proposed algorithm is specified in two criteria, the percentage of success, as represented by the number of trials required for the object function to reach its known target values, for example, we define 0.005 for those target values is 0.

The average value of the solution obtained in all trails.

<table>
<thead>
<tr>
<th>Dimensions of Rastrigin</th>
<th>Target bar of fitness value</th>
<th>IWO</th>
<th>HGIWO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Success Ratio</td>
<td>Mean solution</td>
</tr>
<tr>
<td>10</td>
<td>5</td>
<td>5%</td>
<td>17.6</td>
</tr>
<tr>
<td>20</td>
<td>30</td>
<td>15%</td>
<td>50.2</td>
</tr>
<tr>
<td>30</td>
<td>50</td>
<td>16%</td>
<td>69</td>
</tr>
</tbody>
</table>

Table 2: Simulation results of Rastrigin function

In table 2, we present the performance obtained over all trail runs of HGIWO for Rastrigin function, comparing with IWO. All the readings given are the averages over 100 independent runs per function. Table 2 shows that both IWO and HGIWO are able to handle Rastrigin optimization, but the HGIWO has more successful results than IWO, and better mean solution, although the Rastrigin is a challenging optimization problem, because it has numerous local minima; however the function has just one global minimum, which occurs at the point [0, 0]. A well-tuned IWO performs very well in finding global optima of the benchmark problem, like tuning the Delta initial and delta final values.

In this study each experiment has been repeated 50 times and the mean best fitness of these 50 independent runs has been reported. For comparing different algorithms the first thing we require is a fair different amount of work in their inner loops metric. The number of iterations or generations cannot be used as a time measure as the algorithms perform.

Experiments from other research show that IWO can optimize its global search capability when combined with other algorithm. This proposed HGIWO is capable of preventing local optimization premature and speed up searching ability. Adding hybrid gene to the IWO algorithm, we were able to get a low computational cost while obtaining competitive result on well-known benchmark simulation studies.
4 Conclusions

Locating global minimizers is a very challenging task for any minimization method. In this paper, we have presented a simple and modified version of an integrated algorithm exploiting the features of IWO and EA. The novelty of the present work is the use of diversity for activating the crossover operator. The crossover operator is devised to improve the global searching capability and to enhance the capability of escaping from a local minimum. The empirical results show that the proposed algorithm is quite competent for solving high-dimension functions. However, we would
also like to say that since the results quoted here are based on the empirical study only and we are yet to explore theoretical relevance of the proposed HGIWO, making any concrete judgment does not sound fair. Moreover the platform on which we have conducted the experiments is quite narrow. We are working on the problems with higher dimensions (100 and above). In addition, extensive testing on more complicated real-life optimization tasks like DNA sequence research is necessary to fully investigate the properties.

Less computational time and ease of practical implementation on embedded systems make the proposed algorithm beneficial in real time decision-making situations. For further investigations, the effect of incorporating surveillance to the task assignment problem, communication imperfection and consideration of flyable path instead of Euclidean path can be surveyed.
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