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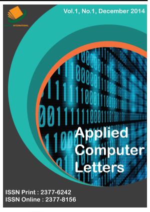

RESEARCH ON NOISYS AND NOISY REDUCTION STRATEGY IN IEC ALGORITHM

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ABSTRACT

The noises in the individual fitness evaluation will be unfavorable to the population evolution in IEC (interactive evolutionary computation), so it restricts extensive application of the algorithm in complicated optimization problem. This paper analyzes the sources of the noises in the IEC genetic algorithm, proposes a 3-phase noisy model based on the definition of the cognition evaluation and fatigue evaluation, then gives the cognition evaluation and fatigue evaluation description based on individual Hamming distance and noisy reduction strategy based on fitness confidence, and finally gives the evolving individual fitness adjustment algorithm.

KEYWORDS

Interactive evolutionary computation, the noisy, strategy of reducing noises

1. INTRODUCTION

The research of the noisy optimization based on the genetic algorithm started in 70s of 20th century and was focused by the scholars in the late period of 80s. The noisy from the genetic algorithm may be from the decision variants or individual fitness measurement, or optimization problem [1]. The noisy mainly affect selection operation in evolution, so the algorithm cannot correctly reserve the evolution information, "development" and "exploration" capability will reduce, and the evolution efficiency is low.

Based on a study, the traditional noisy compensation (noisy reduction) strategy is based on three methods. First, add the sampling time, secondly, increase the population scale; thirdly, improve the genetic operator [2,3]. Markon proposes the selection operation based on the threshold. When the fitness difference between two individuals reaches a threshold, the dominance relation can be identified. Otherwise, it is difficult to evaluate advantages and disadvantages of the individuals with similar fitness [4,5].

The IEC algorithm is affected by noises, which is mainly embodied in the evaluation of evolution individuals, but it is regretful that the existing noisy reduction strategies are not adaptive to the IEC algorithm. The human being is the valuable resources in the IEC algorithm. We cannot add the sampling time and increase the scale of the population. According to a study, it will make personnel fatigue heavier, so the personnel cannot objectively evaluate the evolutionary individuals [6]. Although the improved genetic operations do not require sampling time, the variable-scale mutation and threshold-based selection will increase convergence algebra of the population, it will increase the fatigue degree of the persons.

It is a very feasible problem to study how to reduce influences on the noisy in the IEC algorithm. The noisy "disturbs" the fitness of the evolutionary individuals, so the noisy reduction should start with fitness. The given fitness is not objective due to "disturbance" of the noisy, so it should be properly adjusted according to noisy strength. The noisy strength will change with evolution, so this paper will adjust the person's evaluation on the evolutionary individuals by adopting different strategies according to the evolution phase, so the adjusted fitness can better reflect true performance of the evolutionary individuals.:

2. NOISY OF INTERACTIVE GENETIC ALGORITHMS

For easy description, this paper considers the following optimization problem:

Maximize f(x)

$$x \in S \subseteq R^n \qquad (1)$$

$$F(x,t) = f(x) + \delta(x,t)$$

In this equation, x is D-dimension variant, S is the value scope, f(x) is the optimized performance index and cannot be expressed with the explicit function, δ(x,t) is noisy. Provided that no confusion occurs, the evolutionary individual and search space are marked s x and S. The person assigns the fitness of x with F(x, t) in ith generation.

2.1 The Noisy Source

The noisy of the IEC algorithm is caused by two factors. The first factor is the shift of the individual fitness due to insufficient cognition of a person on the evaluation objects. The second factor is the fluctuation of the evolutionary individual fitness caused by person's fatigue.

The noisy strength of the evolutionary individual fitness will change with the cognition degree of a person on the evaluation object. Generally the persons cannot fully cognize the evaluation object in the initial phase of the population evolution and have no stable evaluation standard, so the evaluation results are not certain. In addition, the fitness given by persons can be regarded to include cognition noisy. After a person evaluates some individuals, it will have comprehensive cognition on the evaluation object and form stable evaluation standard. In addition, the fitness given by a person only includes a small random noisy, but it can truly reflect the advantages and disadvantages of the evaluation individuals. With growth of the population evolution generation, a person will feel fatigue, so it will affect objectiveness of the individual evaluation. According to a researcher, the fitness given by a person can be thought to include the random noisy with incremental strength

From the above analysis, the noisy of the IEC algorithm features phase, non-structure and space dependence.

2.2 The Cognition

As described in the above, the noisy of the IEC algorithm are mainly caused by unfamiliarity of the persons with the evaluation objects on the initial phase of the population. At this time, the fitness given by persons cannot objectively reflect the advantages and disadvantages of the individuals. From the general knowledge of persons on thing cognition, familiarity of the persons on the evaluation objects will gradually deepen with growth of the evaluated evolutionary individuals. According to a research, When the number of the evolutionary individuals evaluated by persons reaches a threshold, they will be fully familiar with this evaluation object [8]. It indicates that the familiarity of persons on the evaluation object should be proportional to the number of the evaluated individuals before the number of the evolutionary individuals reaches this threshold.

Definition: the cognition degree measures the cognition degree of the persons on the evaluation objects. When the number of the evolutionary individuals evaluated by persons reach a threshold, they are fully familiar with this evaluation object.

Based on a study, this threshold is called as the cognition threshold and is marked as Nc [9].

Nc will change with complexity of the evaluation objects. When the evaluation objects are simple, persons can be quickly familiar with the evaluation objects. At this time, Nc is smaller. On the contrary, when the evaluation object is complicated, persons will spend some time in familiarizing the evaluation object. At this time, Nc is bigger. If the current evolutionary individuals evaluated by persons is i+1th individual of ith generation and Ne is marked as the number of the evolutionary individuals evaluated by persons, Ne= (t-1)·N+i. when Ne<Nc, the familiarity of the persons on the evaluation object is proportional to (t-1)·N+i. When Ne≥Nc, persons are fully familiar with the evaluation objects and the given fitness does not include the cognition noisy.

The Change relation of δ(Ne) with Ne is shown in Figure 1.

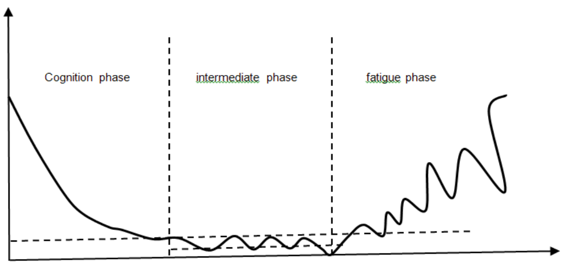

Figure 1: The Change relation of δ(Ne) with Ne

2.3 The Fatigue

Assuming that the persons evaluate each evolutionary individual at same time, when the number of the evaluated evolutionary individuals reaches a threshold, persons will fell fatigue. Later, the fitness given by the persons will fluctuate to some extent and cannot objectively reflect the advantages and disadvantages of the individuals. The fatigue of persons will deepen with growth of the evaluated evolutionary individuals, so the fitness fluctuation strength will continue increasing.

Definition: the fatigue degree can measure the fatigue of persons caused by evaluation of the evolutionary individuals. When the number of the evolutionary individuals evaluated by persons reaches a threshold, they will feel fatigue. This threshold is called as the fatigue threshold and is marked as Nf.

It is easy to know that although persons are familiar with the evaluation objects, persons feel fatigue when (t-1)·N+i≥Nr. later, the fitness given by persons includes the random noisys with incremental strength.

For very complicated evaluation objects, persons may feel fatigue, but they are not fully familiar with them. This case is difficult to handle and is not considered in this paper, namely Nf≥Nc**.**

2.4 The Noisy Function

Based on the above analysis and definition, the δ(x,t) in the Equation (1) can be expressed as the following function on Ne:

$$\delta\left(N_e\right)=\begin{cases} k_1\cdot(N_e-N_c)\ \cdot e^{-Ne},\ N_e<N_c \\ \sigma\cdot e^{-Ne},\ N_c<N_e<N_f \\ k_2\cdot(e^{Ne-Nf})\cdot N(0,1)\ N_e>N_f \end{cases} \qquad (2)$$

In this equation, k1 is the adjustment factor of the corresponding phase. N(0, 1) is the standard normally distributed noisy and k is the noisy strength. The change of δ(Ne) with Ne is shown as the Figure 1. This figure can intuitively indicate that the noisy function has different performances on cognition phase, intermediate phase and fatigue phase.

The above three phases may not occur in the population evolution. Phase occurrence and occurrence time will be related to complexity of evaluation objects and cognition of the persons on the evaluation objects. if the evaluation objects are simple and persons will be familiar with them at the beginning, the population evolution can directly enter the intermediate phase without cognition phase. On the other hand, if the search space is smaller and the evolutionary population can converge when persons need not evaluate massive evolutionary individuals, the population evolution will not experience the fatigue phase, so the Figure 1 includes general noisy on three phases.

3. ADJUSTMENT OF EVOLUTIONARY INDIVIDUAL FITNESS FOR NOISY REDUCTION

3.1 The Idea of Algorithm

Based on the features of the fitness noisys of evolutionary individuals in the IEC algorithm, different strategies will be used on different phases [10]. The fitness of the evolutionary individuals assigned by persons is adjusted and the adjusted fitness participates in genetic operations to reduce influence of the fitness noisys on the population evolution to most extent.

3.2 The Fitness Confidence.

Since the evolutionary individual fitness assigned by persons includes noisy, the fitness given by persons are not trusted or are not fully trusted. We can describe the confidence of the fitness given by persons with the confidence. It is easy to know that the confidence will change with fitness noisy strength. If the noisys are bigger, the confidence of the fitness given persons will be lower. On the contrary, when the noisy strength is smaller, the confidence of the fitness given by persons is higher. When no noisy is available, the confidence of the fitness given by persons is 1, so the confidence function R(Ne) can be expressed as follows:

$$R\left(N_e\right)=\begin{cases} 1-k_1\cdot(N_e-N_c)\ \cdot e^{-Ne},\ N_e<N_c \\ k_2\cdot(e^{-(Ne-Nf)})\ \cdot N(0,1)\ N_e>N_f \\ k_2\cdot(e^{-(Ne-Nf)})\ \cdot N(0,1)\ N_e>N_f \end{cases} \qquad (3)$$

From the Equation (3), peoples gradually familiarize the evaluation object and establish the evaluation standard on the cognition phase, so the confidence of the fitness will increase with growth of the evaluation individuals. After reaching the cognition threshold, the population evolution will enter the intermediate phase. At this time, the individual fitness will include smaller random noisy and the confidence is Figure 1. With growth of the evaluation individuals on the fatigue phase, the fitness noisy strength will gradually increase with the exponential law and random noisys will exist. At this time, the fitness will reduce with growth of the evaluation individuals.

3.3 Identify N_c and N_f

The Equation (3) includes key parameter N_c and N_f, which will determine the phase of the population evolution and further determine the identification method of the confidence of the evolutionary individual fitness given by persons. How are N_c and N_f identified? Since N_c and N_f reflect evaluation of persons on evolutionary individuals, we should start with the gene type and fitness of the evolutionary individuals.

For similar individuals, if the fitness given by persons are very similar, the confidence of the fitness given by persons is high. It indicates that the fitness noisy is smaller and the population evolution is on the intermediate phase. On the contrary, if the fitness given by persons is very different, the confidence of the fitness given by persons is low. It indicates that the fitness noisy is bigger and the population evolution is on the cognition phase or fatigue phase.

The evolutionary individuals use binary coding, if $x_i(t_1)$ and $x_j(t_2)$ indicate ith individual of t th generation and jth individual of t thgeneration in the evolutionary population, the Hamming distance of $x_i(t_1)$ and $x_j(t_2)$ are

$$H(x_i(t_1),x_j(t_2)) = \sum_{k=1}^{i} | x_i(t_1) - x_j(t_2) | \tag{4}$$

Based on the above equation, $x_{ik}(t_1)$ indicates kth gene of $x_i(t_1)$. persons assign the fitness difference of two individuals as:

$$\Delta F(x_i(t_1), x_j(t_2)) = | F(x_i(t_1)) - F(x_j(t_2)) | \tag{5}$$

Based on the person cognition law, for the similar evolutionary individuals, persons will give similar evaluation results in normal case. For very different evolutionary individuals, the evaluation results given by persons are very different, but the case is not like it in abnormal case and different evaluation deviations are available.

Definition: the evaluation deviation is the evaluation deviation of the evolutionary individuals due to persons who are not familiar with evolutionary individuals or feel fatigue. the mathematical expression is described as follows:

$$\begin{aligned}\delta(x_i(t_1), x_j(t_2)) = &| H(x_i(t_1), x_j(t_2)) \\ &- \Delta F(x_i(t_1), x_j(t_2)) |\end{aligned} \tag{6}$$

F_{max} is the upper limit of the evolutionary individual fitness in this equation.

δ_e is the threshold of the evaluation deviation. If persons give similar fitness to the similar evolutionary individuals, or give very different fitness to very different evolutionary individuals, it indicates that the evolutionary individual fitness given by persons is objective. At this time, $\delta(x_i(t_1), x_j(t_2)) \le \delta_e$. Otherwise, if persons give very different fitness to similar evolutionary individuals, it indicates that the evolutionary individual fitness given by persons is not objective. at this time, $\delta(x_i(t_1), x_j(t_2)) > \delta_e$.

For the evolutionary individual $x_i(t)$ to evaluate, the first K adjacent evaluated evolutionary individuals are $x_1, x_2, \ldots, x_k$, the evaluation deviation of xi(t) x1, x2, ..., xk are:.

$$\begin{aligned}&\delta(x_i(t), x_k) = | H(x_i(t), x_{jk}) - \Delta F(x_i(t), x_{jk}) | \\ &k = 1, 2, \ldots, K\end{aligned} \tag{7}$$

K is called as the evaluation deviation tracking depth. generally K∈{l, 2, ..., N}. It indicates that bigger K indicates longer reverse tracking of person evaluation. $\delta(x_i(t), x_k)$ reflects long evaluation deviation of persons. On the contrary, smaller K indicates shorter reverse tracking of the evaluation process of persons. $\delta(x_i(t), x_k)$ reflects short evaluation deviation of persons.

For $\forall k \in$ {1, 2, ..., K}, if $\delta(x_i(t), x_k) \le \delta_e$, it indicates that the population is on the intermediate phase, so the cognition threshold is:

$$\begin{aligned}N_c = min\{&(t-1) \cdot N + i \mid \in \{l, 2, \ldots, K\}, \\ &\delta(x_i(t), x_k) \le \delta_e\}\end{aligned} \tag{8}$$

On the contrary, for ▯k ∈{1, 2, ..., K}, if δ(xi(t), xk)> δe, it indicates that the population is on the cognition phase or fatigue phase. from the sequence of the population evolution process, after the population evolution experiences the intermediate phase, for ▯k ∈{1, 2, ..., K), if δ(xi(t), xk) >δe, it indicates that the population is on the fatigue phase and the fatigue threshold is:

$$\begin{aligned}&N_f = min\{(t-1) \cdot N + i \mid \in \{l, 2, \ldots, K\}, \\ &\delta(x_i(t), x_k) > \delta_e\}\end{aligned} \tag{9}$$

Otherwise, the population is on the cognition phase. After first generation of evolutionary population is evaluated, for ▯k ∈{1, 2, ..., K}, $\delta(x_i(t), x_k) > \delta_e$. To adjust the threshold prior to further population evolution, $N_c=(t+1) \cdot N$, so we can give the equation to identify N_c and N_f.

3.4 Adjustment of evolutionary individual fitness

The fitness noisys make the fitness assigned by persons not trustable or not fully trustable. Based on the discussion in the above two sections, we describe the fitness confidence mathematically. Based on it, we can adjust the evolutionary individual fitness assigned by persons and make the adjusted fitness participate in further genetic operations. Adjustment is described as follows: higher fitness confidence indicates smaller adjustment of the evolutionary individual fitness assigned by persons. On the contrary, the lower fitness confidence indicates bigger adjustment of the evolutionary individual fitness assigned by persons, namely discount of the fitness confidence accepts the evolutionary individual fitness assigned by persons, so the following adjustment equation of the evolutionary individual fitness can be obtained**:**

$$F' x_i(t) = R((t-1) \cdot N + i - 1) \cdot F(x_i(t)) \tag{10}$$

F'xi(t) is the fitness corrected by the evolutionary individual xi(t). the evolutionary individual fitness is corrected centrally after persons evaluate all generations of the populations.

3.5 The Formal Description of The Algorithm

The formal description of the algorithm is shown as follows:

Step 1: identify k1, k2, K and genetic operation parameter and generate initial population:

Step 2: Decode, users evaluate the evolutionary individuals.

Step 3: Compute the evaluation deviation according to the Equation (7).

Step 4: Identify Nc and Nf according to the method in Equation(3).

Step 5: Adjust the individual fitness according to the Equation (10).

Step 6: Check if the algorithm meets stop rule. if it meets, output the optimal individual and terminate the algorithm. Otherwise, skip to the step 7.

Step 7: Perform genetic operation, generate next generation of population and skip to the step 2.

4. CONCLUSIONS

The fitness noisy of the IEC algorithm is not favorable to population evolution and the noisy reduction algorithm for the traditional genetic algorithm is not applicable here. The evolutionary individual fitness given by persons is assigned with different confidences according to the evolution phase of the populations and the evolutionary individual fitness given by persons is adjusted. The adjusted fitness participates in further genetic operation to reduce the fitness noisys. This methods adjusted the person's evaluation on the evolutionary individuals by adopting different strategies according to the evolution phase, so the adjusted fitness can better reflect true performance of the evolutionary individuals.

Notice that persons may give the similar fitness for very different evolutionary individuals. If so, the fitness cannot indicate that the population is on the cognition or fatigue phase. This case is not considered in this paper, so the results are limited. Proper division of population evolution phases will be further studied in future.

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REFERENCES

[1] Takagi, H. 2001. Interactive evolutionary computation: fusion of the capabilities of EC optimization and human evaluation, in Proceedings of the IEEE, 89, (9): 1275-129.

[2] Pretro, A.D., While, L., Barone, L. 2004. Applying evolutionary algorithms to problems with noisy, time-consuming fitness functions, in Proceedings of IEEE Congress on Evolutionary Computation, 1254-1261.

[3] Markon, S. Arnold, D.V., Back, T., Beielstein, T., Beyer, H.G. 2001. Thresholding a selection operator for noisy ES, in Proceedings of IEEE Congress on Evolutionary Computation, 465-472.

[4] Yao, X. 1999. Evolving artificial neural works, in Proceedings of IEEE, 87, 1423-1447.

[5] Liang, C.Y., Huang, Y.Q., Chen, Z.M. 2004. Study on Adaptive Genetic Algorithm for an Integrated Lot-size Model based on VMI, in Proceedings of 2004 International Conference On Management Science and Engineering, 1 (8): 43-48.

[6] Zhou, Y., Gong, G.W., Guo, Y.N. 2008. Algorithm and its application, Control Theory and Application, 25, (2): 223-227.

[7] Beyer, H.G. 2000. Evolutionary algorithms in noisy environments; theoretical issues and guidelines for practice. Computer Methods in Applied Mechanics and Engineering, 186, (2): 239-267.

[8] Zhao, L.J. 2014. IEC algorithms in the Multi objective optimization, Guangzhou, Jinan University press.

[9] Peng, Y.X. 2000. Management decision analysis," Beijing, Science Press.

[10] Yue, C.Y. 2003. The decision theory and method, Beijing: Science Press**.**