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An Improved univariate Marginal Distribution Algorithm for Dynamic Optimization Problem

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Abstract

In dynamic environments, it is difficult to track a changing optimal solution over time. An improved univariate marginal distribution algorithm (IUMDA) is proposed to deal with dynamic optimization problems. This approach is composed of the diffusion model, which uses the information of current population, and the inertia model, which uses the part history information of the optimal solution. After an environment changed, the strategy is changed by a detecting operator to guide increasing the population diversity. Finally an experimental study on dynamic sphere function was carried out to compare the performance of IUMDA and mutation UMDA. The experimental results show that the IUMDA is effective for the function with moving optimum and can adapt the dynamic environments rapidly.

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1.Introduce

Although most of the optimization problems discussed in the scientific literature is static, many real-word problems are dynamic, such as uncertainty dynamic control systems, material processed. In these dynamic optimization problems, the evaluation function (or fitness function) and the constraints may change over time.

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In such cases the optimization algorithm has to track a moving optimum as closely as possible, rather than just finds a single good solution.

It has been argued that evolutionary algorithms (EAs) may be a particularly suitable candidate for this type of problems. However EAs need to be adapted for optimal results on dynamic optimization problems. When the changes occur, the solution given by the optimization procedure may be no longer effective and may actually be misguiding the search. In order to overcome the problems mentioned above, many methods have been proposed [1-8]. Considered above mentions, a new univariate marginal distribution algorithm (IUMDA) is proposed to solve dynamic optimization problems in this paper.

2.Improved Optimization Algorithm

Considered the dynamic multi-objective optimization is as followings:

$$\begin{aligned}&\min f(x,t)=(f_1(x,t),f_2(x,t),\cdots,f_M(x,t))\\&subject\quad to\quad x\in[L,V]\end{aligned} \tag{1}$$

Where t is time variable, x is decision variable, $[L,V]$ is search space, $f(x,t)$ is objective which has the continuous objective function of M and changes with time.

About this problem, the designed aim is that the algorithm must track a changing optimal solution over time when environments are changed. So we must use intelligence optimization algorithm to solve this problems. As the tradition evolutionary algorithms, the continue version of univariate marginal distribution algorithm (UMDA) is one sort of Estimation of Distribution Algorithms and has been applied to many optimization problems [6-7].

In the static environments, the optimal solution $x^*(t)$ of the current population is usually acted as an attractor, which attracts the other individuals move towards the attractor to find the promising region of the optimum. However in the dynamic environments, when the problem changes at the end of generation t, the next optimal solution may move away from $x^*(t)$. In order to find the new optimal solution, the algorithm needs increase the diversity and search new space which is different from the region presented by current population. That is to say the promising region of optimum is away from $x^*(t)$. If the environment changes at the end of generation t corresponding to the k -th change, the optimal solution of the current population is denoted by $x^*(t)$ （$x^*(t)$ is the optimal solution of generation t），it is applied with the following formula to generate new individual x_{new}.

$$x_{new}=x+\lambda_1(x-x^*(t)) \tag{2}$$

Where λ_1 is random number from [0, 1]. According to the diffusion model, if the environment changes at the end of generation t, then $x^*(t)$ can be considered as a repeller rather than an attractor. The reppeller guides the algorithm to search space away from the repeller and to increase the diversity of the population using the current information.

After the environment changed, it will be effective for dynamic optimization to predict the new optimal position by previous optimal solution. Assume that the environment changes at the end of generation t corresponding to the k -th change, the optimal solution of the current population is $x^*(t)$, and then $x^*(t)-x^*(t-1)$ which called velocity of optimal solution at change period $k-1$ is used as the inertia velocity at change period k to predict the next optimal solution. The model is denoted in the following.

$$x_{new} = x + \lambda_2 (x^*(t) - x^*(t-1)) \tag{3}$$

Where $x \in U$ (U is the set of selected individuals), λ_2 is a random number from [0, 1], which denotes the step size to move in direction of $v(k-1)$. From this model, if the prediction is correct, the prediction set aids the population to discover the new optimal solution quickly. In order to detect the environment changed automatically, a detecting operator is proposed as follows:

$$\varepsilon(\tau) = \frac{\sum_{i=1}^{sn} \left\| f(x^i, \tau) - f(x^i, \tau-1) \right\|}{sn \max_{i=1,\cdots,sn} \left\| f(x^i, \tau) - f(x^i, \tau-1) \right\|} \tag{4}$$

Where x^i is individual $i = 1, 2, \cdots sn$, which is choose 10% of the colony dimension. When the $\varepsilon(\tau) > \eta$ (η is a threshold), the environment is changed. Then by using the inertia prediction the algorithm convergence is increased.

Based on the consideration above, the improved approach makes useful of the current information and part history information, and guide the population to search the promising region. Then an improved UMDA (IUMDA) is presented by incorporating UMDA with this approach. The following is the improved algorithm:

Step1. $t \leftarrow 0$, for everyone variable, obtain randomly the parameters of a normal probability distribution for each variable.

Step2. Draw X^t to obtain a population $Pop(t)$ of N individuals;

Step3. Test for change. Calculate $\varepsilon(\tau)$, if the environment no changes, then turn to step 4, otherwise turn to step 6;

Step4. Generate M neighbor individuals of $x^*(t)$ to form the neighbor set U, where the neighbor distance is controlled in [0.05. 0.15];

Step5. Apply the formula (2), an individual will be adjusted the new population;

Step6. Apply the formula (2) and formula (3) on U and get one set of D;

Step7. Estimate the parameters of the new density functions according to $S(t)$.

Step8. Mutate σ_i^{t+1} according to mutation probability;

Step9. If the termination is not satisfied, $t \leftarrow t+1$ go to step 2, otherwise, stop.

3.Experimental Study

In order to test the performance of the proposed algorithm, we used the dynamic sphere function with three dimensions [8]. The function is formulated as:

$$f(x, y, z, t) = (x - \delta_1^k(t))^2 + (y - \delta_2^k(t))^2 + (z - \delta_3^k(t))^2 \tag{5}$$

Where (x, y, z) is a time-invariant "basis" landscape. $(\delta_1^k(t), \delta_2^k(t), \delta_3^k(t))$ are the global optimal solution, which is a time-varying parameter, and moves randomly or period in different trajectories to construct dynamic function. In the above dynamic function, suppose that the environment is periodically changed every τ generation, and then $k = \lfloor t / \tau \rfloor$ is the change period index, where t is the generation counter. According to the different type along which optimal point moves, we can get three different dynamic test functions.

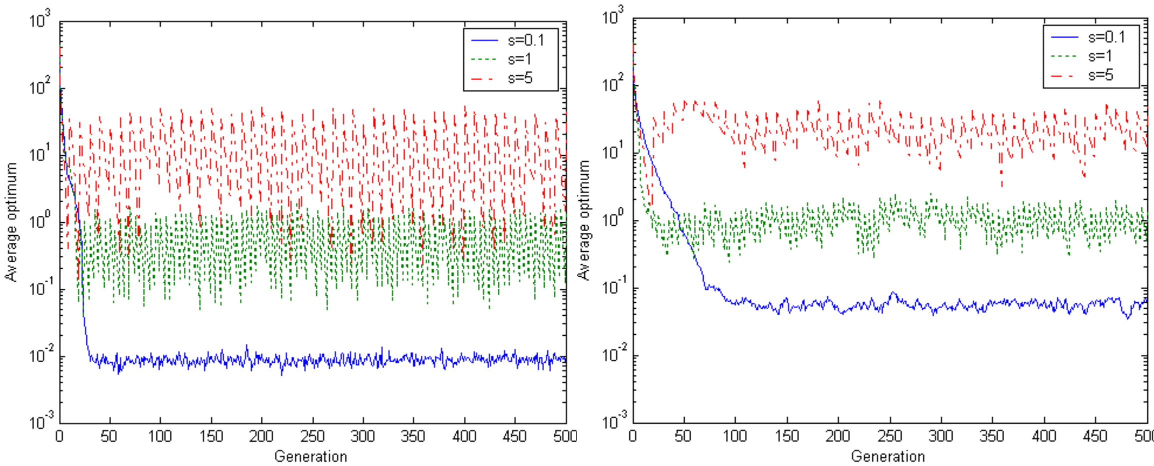
In the dynamic random type, the optimal location is calculated as follows:

$$\delta_m^k = \delta_m^{k-1} + sN(0,1)\,,\quad m = 1,2,3\,,\quad \delta_m^0 = 0 \tag{6}$$

Where $N(0,1)$ is a Gaussian random variable with mean 0 and variance 1. Here the severity parameter determines the variance of the noise added to the previous optimal solution. In this paper, the search space is set to $(-50.0, 50.0)^3$ and T is set to 25. In linear type, when the global optimal location moves past the search space, then the location moves in contrary direction by primary change severity.

Experiments were carried out to compare the performance of the IUMDA and MUMDA on the test environments constructed above. MUMDA is hyper mutation based UMDA, in which hyper mutation is selected to increase the diversity when the problem is changed. In order to compare performance of different algorithms, the total population size N is fixed at 40 individuals. The other parameters are set to $\alpha = 0.5$, $r = 0.2$.

The experimental results on test functions with different dynamic type are plotted in Fig 1 and summarized in Table 1.



(a) The IUMDA results (b) The MUMDA results

Fig.1. Experimental results on random linear type of dynamic functions.

Table 1 Offline error ± standard error for different change severities on random type

Algorithms	Shift severity s and change period τ		
	s =0.1, τ =1	s =1.0, τ =5	s =5.0, τ =10
IUMDA	0.0161 ± 0.0799	0.1190 ± 0.0500	1.3317 ± 1.2206
MUMDA	0.2437 ± 0.8173	0.5768 ± 0.2119	12.6367 ± 7.5438

Figure 1 show the results of average optimum which plotted against generation. In each figure, three dynamic environments are tested by three algorithms. The environmental dynamics parameters are set to s =0.1, τ =1; s =1.0, τ =5 and s =5.0, τ =10 respectively.

From these figures, it can be seen that, generally, IUMDA outperforms MUMDA in the same environment. One straight forward approach to make EAs more suitable for dynamic environments is to increase the diversity after a change. However the random immigrant and hyper mutation approaches increase the diversity by generating the new individuals in the whole search space. Although these two approaches increase the diversity, the diversity is too dispersive to concentrate the promising region of optimum. Thus the computation time needed to track the optimum will be delayed. So in same environment the average optimum of MUMDA is worse than IUMDA. In such cases the improved algorithms has positive effect on the proposed algorithm to adapt the changed environment.

4.Summary

In dynamic environments, it is important that the optimization algorithm is able to continuously track the moving optimum over time. In this paper, we proposed a new approach algorithm to tackle dynamic environments. The objective of the approach is to increase the diversity in a guide fashion after a change. In a dynamic environment, it will be effective to predict the new optimal position by previous optimal solution.

In this paper, because of considering a new strategy for dynamic optimal problems, the proposed method only fits for Dynamic test function, and is good than other MUMDA faintly. To get better optimum results in dynamic environments, the algorithm is to improve in future yet.

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