Chaotic differential evolutionary algorithm

algorithm

chaotic systems

这里展示3个chaotic system

· logistic map

$$ch_{k+1} = uch_k(1 - ch_k), ch_k \in [0, 1], k = 0, 1, 2, \dots, K$$
 (1)

· mapping drawn form chaotic neuron

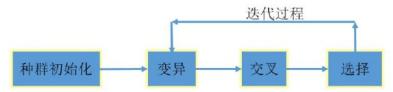
$$ch_{k+1} = \eta ch_k - 2 \tanh(\gamma ch_k) \exp[-3(ch_k)^2], ch_k \in [0, 1], k = 0, 1, 2, \dots, K$$
 (2)

k是迭代计数,K预设最大值,u和 γ 是控制参数, $\eta \in [0,1]$,在式(1)中,设定 $\mu = 4, ch_0 \notin \{0,0.25,0.5,0.75,1\}$,在式(2)中, $ch_0 \notin \{0,0.25,0.5,0.75,1\}$,这样便可利用(1)(2)(3)迭代,无规律,随机地分布式搜索。

Differential evolution algorithm

https://blog.csdn.net/qq 37423198/article/details/77856744] 这里讲的很详细,我也参考着写一下算法过程。 差分进化算法:类似于遗传算法,是其的一种改进。

算法过程



• 初始化 随机产生M个个体一,每个个体由n维向量组成(也说成染色体)

$$X_i(0) = (x_{i,1}(0), x_{i,2}(0), x_{i,3}(0)), \dots, x_{i,n}(0), i = 1, 2, 3, \dots, M$$

第i个个体的第j维取值方式如下:

$$X_{i,j}(0) = L_{j_min} + rand(0,1)(L_{j_max} - L_{j_min}), i = 1,2,3,\ldots,M \ j = 1,2,3,\ldots,n$$

在第g次迭代中,从种群中随机选择3个个体 $Xp_1(g), Xp_2(g), Xp_3(g)$,且 $p1\neq p2\neq p3\neq i$,生成的变异向量为:

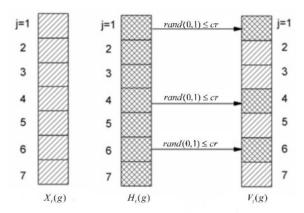
$$H_i(g) = X_{p1}(g) + F \cdot (X_{p2}(g) - X_{p3}(g))$$

这里的F是缩放因子

交叉

$$v_{i,j} = \left\{egin{array}{l} h_{ij}(g), rand(0,1) \leq cr \ & x_{ij}(g), else \end{array}
ight.$$

其中, $cr \in [0,1]$ 为交叉概率



• 选择

$$x_i(g+1) = \left\{ egin{aligned} v_i(g), if \, f(v_i(g)) < f(X_i(g)) \ x_i(g), \, else \end{aligned}
ight.$$

• 参数 f 是适应度函数,M一般介于 $5 \times n$ 到 $10 \times n$ 之间, 不能少于4;F一般在[0,2] 间选择,通常取0.5,cr 一般在[0,1]间选择,一般选0.3

• 参数自适应调整 将随机选择的个体从优到劣排序,得到 X_b, X_m, X_w ,对应适应度 f_b, f_m, f_w ,变异算子改为:

$$V_i = X_b + F_i \cdot (X_m - X_w)$$

F的自适应变化:

$$F_i = F_l + (F_u - F_l) \cdot rac{f_m - f_b}{f_w - f_b}$$

其中, $F_l = 0.1, F_u = 0.9$

$$cr_{i} = \begin{cases} cr_{l} + (cr_{u} - cr_{l}) \frac{f_{i} - f_{min}}{f_{max} - f_{min}} & \text{if } f_{i} > \bar{f} \\ cr_{l} & \text{if } f_{i} < \bar{f} \end{cases}$$

其中 f_i 是个体 X_i 的适应度, f_{min} 和 f_{max} 分别是当前种群中最差和最优个体的适应度, \bar{f} 是当前种群适应度平均值, cr_l 和 cr_u 分别是cr的下限和上限,一般 $cr_l=0.1, cr_u=0.6$ 。

变异策略表示为DE/a/b, 其中a表明被变异个体的选择方式, b表明差向量的个数。

DE/rand/1:

$$V_i = X_{v1} + F(X_{v2} - X_{v3})$$

② DE/best/1:

$$V_i = X_{best} + F\left(X_{p1} - X_{p2}\right)$$

DE/current to best/1:

$$V_i = X_i + F\left(X_{best} - X_i\right) + F\left(X_{p1} - X_{p2}\right)$$

OE/best/2:

$$V_i = X_{best} + F(X_{p1} - X_{p2}) + F(X_{p3} - X_{p4})$$

OE/rand/2:

$$V_i = X_{p1} + F(X_{p2} - X_{p3}) + F(X_{p4} - X_{p5})$$

cpde

使用chaotic system初始化

Algorithm 2 (Chaotically initializing population)

Step 0. Set the maximum number of chaotic iteration $K \ge 300$, the population scale NP, and the individual counter i = 0.

While $(i \leq NP)$ do

- Step 1. Randomly initialize variables $ch_0^j \in (0,1), ch_0^j \notin \{0.25, 0.5, 0.75\}, j = 1, 2, ..., n$ and set iteration counter k = 0.
- Step 2. While (k < K) do

 Generate different chaotic variables $ch_k^j, j = 1, 2, ..., n$ according to the formula (1), (2) or (3). Set k = k + 1.

End while.

Step 3. Mapping the chaotic variables ch_k^j to feasible region according to equation $x_{ij}^{(0)} = x_{\min,j} + ch_k^j(x_{\max,j} - x_{\min,j}), j = 1, 2, \dots, n.$

Step 4. Set i = i + 1

End while

Note that in Algorithm 2, a point (individual) in feasible region is generated through one chaotic system through K cycles of Step 1 to Step 3. And a population with NP individuals is formed after NP cycles of Step 1 to 4.

cpde算法

chaotic部分:初始化,在交叉后用chaotic产生的个体替换差的那一半个体,再用pattern search方法对最优个体进行优化,再使用获得的个体替换当前最着的那一半个体。

Algorithm 3 (The new algorithm (CPDE))

- Step 0. Preset the population size, NP, the maximum number of iteration, ktoal within DE algorithm, and the maximum iteration TT_{max} . Set T=0.
- Step 1. Chaotically initialize the population (see Algorithm 2) and evaluate it.
- Step 2. While (TT_{max}) or solution with preset precision not reached) do
 - Step 2.1. Execute first selection, mutation, crossover, second selection of DE search in Section 2.3 for *ktoal* iterations.
 - Step 2.2. Execute the pattern search in Section 2.2 with the best individual in the population as the initial point. Assume x^* is obtained.
 - Step 2.3. Use the chaotically initializing population method (Algorithm 2) to generate a subpopulation S_{sub} with scale NP/2, Use S_{sub} to replace the worst half part of the original population, while the best half part keeps steady in the population.
 - Step 2.4. Use x^* obtained in Step 2.2 to replace the worst individual in the current population and form a new population.
 - Step 2.5. Set T = T + 1 and turn to Step 2.1

End while

Step 3. Output the best results.

引用:

Wang Y J, Zhang J S. Global optimization by an improved differential evolutionary algorithm.[J]. Applied Mathematics & Computation, 2007, 188(1):669-680.