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Geometric Constraint Solving Based on Cell Membrane Optimization

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Abstract: Geometric constraint problem is equivalent to the problem of solving a set of nonlinear equations substantially. The constraint problem can be transformed to an optimization n problem. We can solve the problem with cell membrane optimization. By studying the characteristics of cell membrane and the mode of material transfer, proposed a new global optimization algorithm: Cell Membrane Optimization (CMO), combined with global optimization algorithm. The experiment shows that it can improve the geometric constraint solving efficiency and possess better convergence property than the compared algorithms.

Key words: Geometric constraint solving, cell membrane optimization, global optimization, intelligent computing

INTRODUCTION

The parametric design is a geometric constraint-solving problem. Geometric constraint solving approaches are made of three approaches: algebraic-based solving approach based solving approach and graph-based solving approach (Bo, 1999). One constraint describes a relation that should be satisfied. Once a user defines a series of relations, the system will satisfy the constraints by selecting proper state after the parameters are modified. The idea is named model-based constraints. Constraint solver is a segment for the system to solve the constraints.

In the recent decades, it has seen many new optimization algorithms about the global optimization. For example, Genetic algorithms was put forward by simulating the natural selection of Darwin's biological evolution theory and the biological evolution of genetic mechanism (Holland, 1975). Ant colony optimization algorithm was inspired by ant foraging (Colorni *et al*., 1991). PSO was put forward by simulating the flight behavior of birds (Kennedy and Eberhart, 1995). In order to achieve optimization, the Artificial Fish School Algorithm constructed artificial fish to imitate the fish feeding, clusters, rear-end and random behaviors (Xiaolei, 2003). Leapfrog algorithm was proposed through the simulation of the frogs' feeding characteristics (Eusuff and Lansey, 2003). Migration algorithm is simulated the migration mechanism-population is transferred with the economic center of gravity and is spread with the increasing population pressure to achieve global optimization (Zhou and Mao, 2003). Colony algorithm is proposed mainly based on the characteristics of bees seeking nectar (Karaboga, 2005).

This paper studies the characteristics of the cell membrane and its material transfer methods, from which construct optimization model. Combined with the basic idea of global optimization algorithms, we propose a new global optimization algorithm optimization as Cell Membrane Optimization (Tan and Yu, 2011).

CELL MEMBRANE OPTIMIZATION

According to the process of membrane transport material, the material is divided into three types: fat-soluble substances, high concentrations non-fat-soluble material (HS) and low concentrations non-fat-soluble material (LS) in this paper. In solving optimization problems, a material is corresponding to a solution of the optimization problem, the three different types material are corresponding to three solutions which of different characteristics.

This paper studies is for the unconstrained function optimization problem, as form (1) described.

$$\begin{cases} \min f(x) \\ \text{s.t.} \quad x \in [l \quad u] \end{cases} \tag{1}$$

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In it:

$$[l \quad u]:\{x \in R^n | l_k \le x_k \le u_k, k = 1,...,n\}$$

Suppose form (1) always has solution, i.e., the global optimum exists. The overall process of Cell Membrane Optimization (CMO) is as follows.

Initial the material: In the solution space:

$$S = \prod_{k=1}^{n} [l_k, u_k]$$

Randomly generated m n-dimensional material, every material are randomly distributed in the solution space, calculate the value of their function and keep the best material in the X^{best}.

Classified material type: First, the function value of each material sorted from small to large, material at the top Ps percentage is divided into fat-soluble substance, the material at the back is classified as non-fat-soluble substances; and then the non-fat-soluble material is further divided into two types: high concentration and low concentration. For a substance Y, the concentration of which is defined as the percentage of the material contained in the neighborhood for the total number of the material. As form (2) shows:

$$MeanCon = \frac{1}{m}\sum_{i=1}^{m} Con^i \tag{2}$$

where, n means the number of the material of X^i (i=1, …, m) whose distance from the Y is less than r×(u - l) (it is for any k, with):

$$\left| x_k^i - Y_k \right| < r \times (u_k - l_k)$$

The average of all concentration is MeanCon, as form (3) shows:

$$MeanCon = \frac{1}{m}\sum_{i=1}^{m} Con^i \tag{3}$$

Free diffusion of fat-soluble substances: If f (newfsX^i) is better than (fsX^i), then use newfsX^i to replace fsX^i. Then shrink the search radius vector: $Radius_1 = Radius_1 \times Pb$, repeat this process until max {$Radius_{1k}$, ∀k}>Pa. At the start, the calculate method of the search radius $Radius_1$ is shown in form (4):

$$Radius_1 = \frac{u - l}{2 \times m_1} \tag{4}$$

The correct method of search range is that for k, if $newfsX_k^i > u_k$, then $newfsX_k^i = u_k$; if $newfsX_k^i < l_k$, then $newfsX_i^k = l_k$. The scope correction of the new material appeared below use the same method, no specific description.

High concentrations non-fat-soluble substances diffusion: Assuming that the probability that each high concentrations non-fat-soluble existences carrier is same, set the probability is P_{c1}, if the randomly generated number rand()≤P_{c1}, rand() is between 0 and 1; then the substance (such as hsX^i) can help the movement to spread from high concentration to low concentration side and to make the new location as the local search center (denoted hsXC^i); otherwise make the original place as the local search center. Then, the substance will do locn times local search campaign. Before this the search radius vector Radius2 need to be initialized. The method shown in form (5):

$$Radius_2 = \frac{u - l}{2 \times m_2} \tag{5}$$

Then made locn times random movement (that is generate locn material) in the search area where hsXC^i as the center and $Radius_2$ as radius and corrected their search area. Record the optimal material besthsX^i of the locn material. If f (besthsX^i)< f(hsXC^i), then use besthsX^i to replace hsX^i, or use hsXC^i to replace hsX^i.

Low concentrations non-fat-soluble substances diffusion: Assuming that the probability that each low concentrations non-fat-soluble existences carrier is same, set the probability is P_{c2}. Every low concentrations non-fat-soluble owns energy and the energy value is in [0, 1]. First calculated the function value f (lsX^i) (i = 1, ..., m3) for each low concentrations non-fat-soluble substances, then sort the function value from small to large. For the material that has the minimum function value, its energy E^i is E_{min}, For the material that has the largest function value, its energy E^i is E_{max}, the energy E^i of other substances is between E_{min} and E_{max} and is calculated with a linear order. Which, E_{min} and E_{max} is the constant in [0, 1], here, E_{min} is equal to 0, E_{max} is equal to 1.

If a substance (such as lsX^i) carrier and there is enough energy, then it can be active transport, from the low concentration side to the high concentration side and to make a new location to be the center of the local search (denoted lsXC^i), or the original place to be the local search center. After the active transport, the new location (lsX^i) of the low concentrations non-fat-soluble substances (lsXC^i) is shown in form (6):

$$lsXC^i = lsX^i + (X^{best} - lsX^i)\,(0.5 + 0.5 \times rand()) \quad (6)$$

Then, initial the search radius vector $Radius_3$, as is shown in form (7):

$$Radius_3 = \frac{u - l}{2 \times m_3} \quad (7)$$

Then made locn times random movement (that is generate locn material) in the search area where $lsXC^i$ as the center and $Radius_3$ as radius and corrected their search area. Record the optimal material $bestlsX^i$ of the locn material. If $f(bestlsX^i) < f(lsXC^i)$, then use $bestlsX^i$ to replace lsX^i, or use $lsXC^i$ to replace lsX^i.

Update the material: Use the new material group that composed by the fat-soluble substances, high concentration non- fat-soluble substances and low concentrations non-fat-soluble substances to replace the old material groups X^i (i=1, …, m).

GEOMETRIC CONSTRAINT SOLVING

The constraint problem can be formalized a-s (E, C) (Sheng-Li *et al*., 2003), here E = (e_1, e_2, ……, e_n), it can express geometric elements, such as point, line, circle, etc; C = (c_1, c_2, …, c_m), c_i is the constraint set in these geometric elements. Usually one constraint is represented by an algebraic equation, so the constraint can be expressed as follows:

$$\begin{cases} f_1(x_0, x_1, x_2, \ldots, x_n) = 0 \\ \ldots \\ f_m(x_0, x_1, x_2, \ldots, x_n) = 0 \end{cases} \quad (8)$$

X = (x_0, x_1, …, x_n), X_i are some parameters. Constraint solving is to get a solution x to satisfy formula (8):

$$F(X_j) = \sum_{1}^{m} |f_i| \quad (9)$$

Apparently, if X_j can satisfy F (X_j) = 0, then X_j can satisfy formula (8). So the constraint problem can be transformed to an optimization problem and we only need to solve min (F (X_j))<ε.ε is a threshold.

APPLICATION INSTANCE

In CMO, there are eight adjustable parameters: the maximum iteration generation G is generally in [10, 100]; the local search time locn of no-fat-soluble substance is generally in [10, 100]; Material total quantity m is generally in [10, 50]; the percentage in the colony of fat-soluble substances Ps is generally in [0.1, 0.3]; the threshold to stop thread of fat soluble substance Pa is generally in [1e-6, 1e-3]; the constringency rate of search radius is in [0.8, 0.99]; High and low concentration no-fat-soluble substance in a carrier P_{c1}, P_{c2} is generally in [0.2, 0.8]. The radius r for substance concentration for an algorithm performance is less affected, can be set as a constant. It is not included in the programmable parameters, is generally in [0.2, 0.5].

The two graphs in Fig. 1 are drafts in engineering design. Figure 1b is an auto-produced graph after some sizes of the Fig. 1a are modified by CMO. In this instance, the parameters are set G = 20, locn = 10, m = 20, Ps = 0.2, Pa = 1e-5, Pb = 0.9, P_{c1} = 0.8, P_{c2} = 0.5, r = 0.4, respectively. From the Fig. 1 we can realize from the above figures that once a user defines a series of relations, the

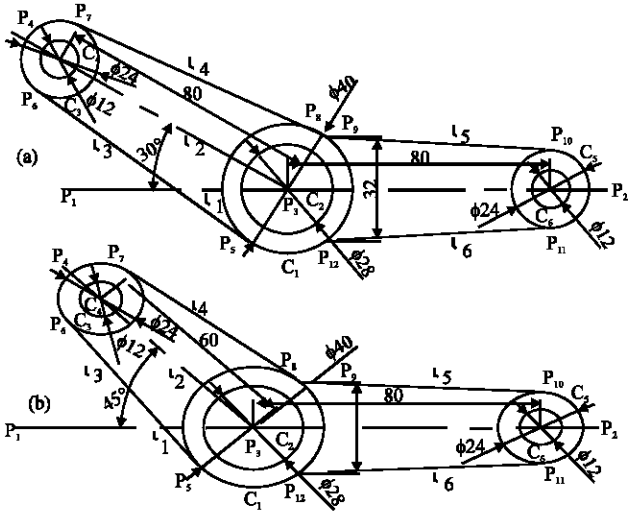

Fig. 1(a,b): (a) A design instance (b) Solving result

system will satisfy the constraints by selecting proper state after the parameters are modified by CMO.

CONCLUSION

Geometric constraint solving is the core of parameterization design. Geometric Constraint Solving is the key of parameterization design system. In this paper the geometric constraint equation set will be transformed into an optimization model. The constraint problem can be transformed to an optimization n problem. We propose a new global optimization algorithm-Cell Membrane Optimization. The efficiency and practicality of the algorithm can be indicated by applying Cell Membrane Optimization. The future work is to prove the convergence from mathematics angle and the influence of related parameters.

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