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Research on the Algorithm for Solving Unconstraint Optimization Problems Utilizing Knowledge Evolution Principle

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Abstract: Based on the evolutionary epistemology idea, an algorithm called UOP-KEA for solving unconstraint optimization problems utilizing knowledge evolution principle is proposed in this study. The main idea of this algorithm can be described as follows. Firstly, an initial knowledge base is formed. The next work is to inherit excellent knowledge individuals by inheritance operator, produce new knowledge individuals by innovation operator, update knowledge base by update operator and accordingly the knowledge evolution is realized. At last, the problem's optimal solution can be gained from the optimal knowledge individual. Experiments were taken on optimization of unconstraint nonlinear test functions. The successful experimental results show that this algorithm is feasible and valid. The algorithm can search the global optimal solution with less population and less reiteration. The global convergence speed and the global optimal solution quality are all satisfactory.

Key words: Knowledge evolution, inheritance operator, innovation operator, update operator, unconstraint optimization

INTRODUCTION

Knowledge is one of human being's own concepts which belong to epistemology. It is the accumulation or induction of experience and contains almost all the meaning of data, information, knowledge and intelligence (Zhu, 2000; Zhong, 2007). In the course of human evolution, knowledge played a vital role. Human had to obey the natural law, at the same time, formed a knowledge system gradually. The knowledge system had a great influence on human evolution and made human evolution rise rapidly. The famous science-philosopher Karl. Popper (Liu *et al*., 2007; Shu and Zuo, 2005; Fu *et al*., 2005) thought that the selection of scientific theory was similar to Darwin's natural selection. Our knowledge is always constituted by hypothesis and passed in the struggle to survive down and showed its relative adaptability. The hypothesis which didn't adapt was eliminated in the competition. Karl Popper put biological evolution together with scientific development, explained how the science evolve and created his knowledge evolutionism. Knowledge evolutionism tells us that knowledge can be regarded as a changing objective knowledge world, in which there is no eternal, immutable knowledge. That is to say, knowledge is incomplete, knowledge itself evolves ceaselessly and its evolution result is close to the truth.

At present, the research on natural computing theory largely focused on the biological natural selection level (Liu *et al*., 2007; Huang *et al*., 2007), which start from the simulation of simple biological evolution. For knowledge evolution, there are quite a number of scholars have done some research work (Zhu, 2000; Xu and Zhao, 2006; Bowonder and Miyake, 2000; Thomas, 2009; Fikret, 2009; Bert, 2009; Menicucci, 2006; Deborah, 2003). But most of them only research on knowledge acquisition, knowledge update, the mechanism of knowledge evolution and the architecture of knowledge management system from the view of philosophy and sociology theory. Based on the evolutionary epistemology idea, an algorithm (called UOP-KEA) for solving unconstraint optimization problems utilizing knowledge evolution principle is proposed from the view of natural computation theory in this study.

BASIC IDEA OF THE ALGORITHM FOR SOLVING UNCONSTRAINT OPTIMIZATION PROBLEMS UTILIZING KNOWLEDGE EVOLUTION PRINCIPLE

Philosophical basis of the algorithm: The algorithm for solving unconstraint optimization problems utilizing knowledge evolution principle (UOP-KEA) is based on Karl Popper's knowledge evolutionism. Karl Popper (Liu *et al*., 2007; Shu and Zuo, 2005; Fu *et al*., 2005)

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thought: the choice of scientific theory is similar to Darwin's natural choice, our knowledge is constituted from hypothesis, it survives from the struggle and shows its relative adaptability and the un-adaptive hypothesis is eliminated in the competition. So, there are two mechanisms in knowledge evolution, one is the productive mechanism of new knowledge and the other is the natural choice mechanism of selecting the superior and eliminating the inferior. This is the same as creature evolution.

Knowledge evolution is always a course which is either long or short, it tends to be developed. The most important sign of the evolution of scientific knowledge is that the truth is improved continuously. Let, N denotes the truth of new knowledge and P denotes the truth of old knowledge, only when N>P can we say that new knowledge surpasses old knowledge and knowledge evolution appears.

Basic idea of the algorithm: The basic framework of the algorithm for solving unconstraint optimization problems utilizing knowledge evolution principle (UOP-KEA) is shown in Fig. 1. Its key operators include inheriting operator, innovation operator and update operator. The main idea of UOP-KEA can be described as follows. Firstly, a knowledge base is formed after the actual area problems have been analyzed and solved. The knowledge individuals in knowledge base are sorted according to their fitness. Based on the initial knowledge base, inheritance operator is used to inherit excellent knowledge individuals so that they can be retained in the next generation. Innovation operator is used to produce new knowledge individuals and a new knowledge set is formed. Update operator is used to update the old knowledge base and form a new knowledge base after evolution. Repeat the above process until the accuracy requirement of problem is met with or the maximum evolution generation number is reached. At last, the optimal solution of problem can be gained from the optimal knowledge individual in knowledge base when the algorithm stops.

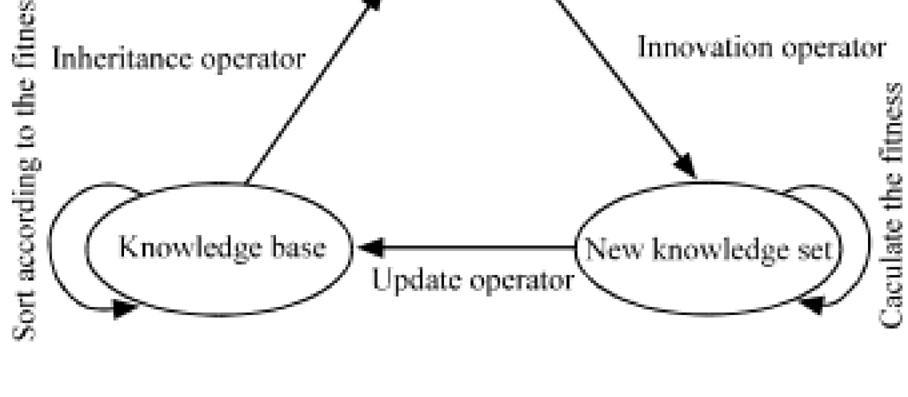

Fig. 1: The basic framework of UOP-KEA

REALIZATION OF THE ALGORITHM FOR SOLVING UNCONSTRAINT OPTIMIZATION PROBLEMS UTILIZING KNOWLEDGE EVOLUTION PRINCIPLE

Structure of knowledge base and coding method of knowledge individual: In the knowledge base of this paper, the contents of knowledge individual include the solution of problem, the information of variable range and the individual fitness, etc. The structure of knowledge individual includes three parts which may be described as (S, V, F). The meaning of S, V and F can be explained as follows:

$$S = \{s_1^t, s_2^t, \cdots, s_G^t\}$$

is the set of feasible solutions of problems. Where, G is the scale of knowledge base, S_i^t denotes the feasible solution in number i knowledge individual (descending order according to the fitness) in the knowledge base of generation t.

$$V = \langle V_1, V_2, \cdots, V_n \rangle$$

is the set of the information of variable range. Where, n is the number of variables. Vi = (I, L, U) denotes the information of variable range $I = [l, u] = \{x | l \le x \le u\}$, l and u denote the minimum and maximum of variables respectively and their initial values are determined by the problem's variable range. L is the objective function value which is corresponding with the minimum u of variables. U is the objective function value which is corresponding with the maximum u of variables. L and U are all initialized a large enough positive real number in this study.

$$F = \{f_1^t, f_2^t, \cdots, f_G^t\}$$

is the set of the fitness of knowledge individuals. Where, f_i^t denotes the fitness of number i knowledge individual in the knowledge base of generation t.

In traditional evolutionary algorithm, the commonly used coding methods include binary coding, real coding, symbol coding and etc. (Wang and Cao, 2002; Li *et al.*, 2002; Zhou and Sun, 1999). In this study, real coding method is used to descript the knowledge individuals. Knowledge base may be regarded to be constituted with G (the scale of knowledge base) real vectors $X_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,w})$ whose dimension number is w. Where, w is the number of attributes of knowledge individual, I = 1, 2,..., G. $x_{i,j}$ denotes the value of number j attribute of number i knowledge individual.

Evolution operators: inheritance operator: The role of inheritance operator is to select a fixed number of excellent individuals from the existing knowledge base and put them into the evolution pool. These selected individuals will participate in a new round of knowledge evolution. Because only the minimum optimization problem is considered in this study, so, the fitness function (fit) x used to evaluate knowledge may be selected as follows:

$$\text{Fit}(x) = \begin{cases} P - \text{obj}(x), & \text{IFobj}(x) < P \\ 0, & \text{IFobj}(x) \geq P \end{cases} \tag{1}$$

where, obj (x) denotes the objective function value which is corresponding with the individual. P is a Pre-set large enough positive number.

Innovation operator: The role of innovation operator is to generate new knowledge individuals. There are two aspects as follows:

On the one hand, there is an innovation for the information of variable range. Based on the relationship between the variable value (or objective function value) of current generation and the boundary value of the corresponding variable in the outstanding individuals (or its objective function value), the information of variable range is adjusted. The innovation rule is:

$$l_j^{t+1} = \begin{cases} x_{i,j}^t, & \text{IF} x_{i,j}^t \leq l_j^t \text{OR} \text{obj}(x_i^t) < L_j^t \\ l_j^t, & \text{Otherwise} \end{cases} \tag{2}$$

$$L_j^{t+1} = \begin{cases} \text{obj}(x_i^t), & \text{IF} x_{i,j}^t \leq l_j^t \text{OR} \text{obj}(x_i^t) < L_j^t \\ L_j^t, & \text{Otherwise} \end{cases} \tag{3}$$

$$u_j^{t+1} = \begin{cases} x_{i,j}^t, & \text{IF} x_{i,j}^t \geq u_j^t \text{OR} \text{obj}(x_i^t) < U_j^t \\ u_j^t, & \text{Otherwise} \end{cases} \tag{4}$$

$$U_j^{t+1} = \begin{cases} \text{obj}(x_i^t), & \text{IF} x_{i,j}^t \geq u_j^t \text{OR} \text{obj}(x_i^t) < U_j^t \\ U_j^t, & \text{Otherwise} \end{cases} \tag{5}$$

On the other hand, there is an innovation for the changing step size and direction of variable. Based on the relationship between the variable value of current generation and the boundary value of the corresponding variable in the outstanding individual, the changing step size and direction of variable are adjusted. The innovation rule is:

$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^t + \left|u_j^t - l_j^t\right| \cdot \alpha, & \text{IF} x_{i,j}^t < l_j^t \\ x_{i,j}^t - \left|u_j^t - l_j^t\right| \cdot \beta, & \text{IF} x_{i,j}^t > u_j^t \\ x_{i,j}^t + (1 - \frac{a}{b})(u_j^t - l_j^t) \cdot \gamma, & \text{Otherwise} \end{cases} \tag{6}$$

In Eq. 2-6, $x^t_{i,j}$ and $x^{t+1}_{i,j}$ denote number j variable in number i knowledge individual of generation t and generation t+1, respectively. l^t_j and l^{t+1}_j denote the minimum of number j variable in the outstanding individual of generation t and generation t+1, respectively. U^t_j and u^{t+1}_j denote the maximum of number j variable in the outstanding individual of generation t and generation t+1, respectively. L and L^{t+1}_j denote the objective function value which is corresponding with the minimum of number j variable in the outstanding individual of generation t and generation t+1, respectively. U^t_j and U^{t+1}_j denote the objective function value which is corresponding with the maximum of number j variable in the outstanding individual of generation *t* and generation t+1, respectively. α and b denote the fitness of number i knowledge individual and the outstanding individual of generation t, respectively. $\alpha, \beta, \gamma \in (0, 1)$.

Update operator: The role of update operator is to update the former knowledge base with excellent new knowledge individuals and gain the new knowledge base after evolution. Assume that the new knowledge set after evolution of generation t is $X'^t = \{x'^t_1, x'^t_2, \cdots, x'^t_M\}$, where, M is the evolution scale. The knowledge individuals in the former knowledge base were sorted according to the fitness, so, the knowledge individual with the lowest fitness of generation t may be recorded as x^t_G. That is:

$$x_G^t = \arg \min_{k=1,2,\cdots,G} (f(x_k^t)) \tag{7}$$

The update rule of knowledge base is:

$$\{x_i'^t \in X^{t+1} \left| f(x_i'^t) > f(x_G^t), \text{AND} x_i'^t \neq x_k^t \right.\} \tag{8}$$

Where, k = 1, 2, ..., G.

In order to maintain the unchanged scale G of knowledge base, the new knowledge individual and the original knowledge individual in knowledge base are sorted according to the descending order of fitness. The former G individuals with higher fitness are retained and the other individuals with low fitness are deleted.

Steps of the algorithm: The realization steps of UOP-KEA can be described as follows:

- **Input:** Knowledge individuals in the initial knowledge base
- **Output:** The optimal knowledge individual in the knowledge base after evolution
- **Step 1:** Let t = 0

- **Step 2:** Initialize knowledge base. For a given problem, an initial knowledge base is formed according to the value range, the structure of knowledge base and the code mode of knowledge individuals
- **Step 3:** Calculate the fitness of knowledge individuals and sort them according to their fitness
- **Step 4:** Judge whether the termination conditions are met or not? If yes, turn to step 10. Otherwise, execute the next step
- **Step 5:** Knowledge's inheritance. Let inheritance operator plays a role on the knowledge population. A number of excellent individuals are selected and put into the knowledge evolution pool
- **Step 6:** Knowledge innovation. Let innovation operator plays a role on the knowledge individuals in the evolution pool. New knowledge individuals are generated and the new knowledge set is formed
- **Step 7:** Calculate the fitness of new knowledge individuals
- **Step 8:** Update Knowledge base. With the help of the update operator, the old knowledge base is updated by the new knowledge individuals and a new knowledge base is formed after evolution
- **Step 9:** Let t = t+1 and turn to step 4
- **Step 10:** Gain the optimal solution of problem from the optimal knowledge individual
- **Step 11:** Stop

SIMULATION EXPERIMENT

In order to test the performance of algorithm, evaluate its feasibility and effectiveness, 10 representative non-linear unconstrained test functions (Li *et al*., 2002; Zhou and Sun, 1999) are selected. The UOP-KEA proposed in this paper is used to search their optimal minimum, respectively. These test functions are shown as follows:

De joug function:

$$f_1 = \sum_{i=1}^{20} x_i^2$$

where, $-5.12 \le x_i \le 5.12$

This function has a global minimum value 0 at point $(x_1, x_2,..., x_{20}) = (0, 0,..., 0)$.

De Jong function:

$$f_2 = 100\cdot(x_{21}-x_2)^2+(1-x_1)^2$$

where, $-2.48 \le x_1, x_2 \le 2.048$

This function has a global minimum value 0 at point $(x_1, x_2) = (1,1)$. Being a pathological function, it is difficult to search the global minimum value for the function.

De Jong function:

$$f_3 = [0.002 + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2}(x_i - a_{ij})^6}]^{-1}$$

where, $-65.536 \le x_1, x_2 \le 65.536$,

$$[a_{ij}] = \begin{bmatrix} -32 -16\ \ 0\ \ 16\ \ 32\ -32 -16 \cdots 0\ 16 32 \\ -32 -32 -32 -32 -32 -16 -16 \cdots 323232 \end{bmatrix}$$

This function is a multi-peak function with 25 local minimum points, but it has only one global minimum point $(x_1,x_2) = (-32,-32)$. The global minimum value is 0.998.

Bobachevsky function:

$$f_4 = x_1^2 + 2x_2^2 - 0.3\cdot\cos(3\pi x_1) - 0.4\cdot\cos(4\pi x_2) + 0.7$$

where, $-1 \le x_1, x_2 \le 1$

This function has a global minimum value 0 at point $(x_1, x_2) = (0, 0)$.

Schaffer function:

$$f_5 = 0.5 + \frac{\sin^2\sqrt{x_1^2 + x_2^2} - 0.5}{[1.0 + 0.001\cdot(x_1^2 + x_2^2)]^2}$$

where, $-100 \le x_1, x_2 \le 100$

This function has a global minimum value 0 at point $(x_1, x_2) = (0, 0)$.

Rastrigin function:

$$f_6 = 200 + \sum_{i=1}^{20}[x_i^2 - 10\cdot\cos(2\pi x_i)]$$

where, $-5.12 \le x_1 \le -5.12$.

This function has a global minimum value 0 at point $(x_1, x_2,..., x_{20}) = (0, 0,..., 0)$.

Six-Hump Camel Back function:

$$f_7 = (4 - 2.1x_1^2 + \frac{1}{3}x_1^4)\cdot x_1^2 + x_1\cdot x_2 + (-4 + 4x_2^2)\cdot x_2^2$$

where, $-3 \le x_1 \le 3, -2 \le x_2 \le 2$

Table 1: Parameters of UOP-KEA

Function	n	obj* ()	T	G	M
f_1	20	0	300	50	20
f_2	2	0	400	30	10
f_3	2	0.998	300	30	10
f_4	2	0	200	30	10
f_5	2	0	300	30	10
f_6	20	0	300	50	20
f_7	2	-1.0316	200	30	10
f_8	2	3	300	30	10
f_9	2	-1	200	30	10
f_{10}	2	-186.7309	300	30	10

Table 2: Test results of UOP-KEA

Function	$obj_{AV}()$	T_{AV}	R_{CONV} (%)
f_1	0	80.3	100
f_2	0	195.2	100
f_3	0.998005	32.7	100
f_4	0	38.0	100
f_5	0	56.1	100
f_6	0	85.0	100
f_7	-1.031616	29.3	100
f_8	3	31.2	100
f_9	-1	28.0	100
f_{10}	-186.730904	56.2	100

This function has 6 local minimum points, but it has only two global minimum points: $(x_1, x_2) = (-0.0898, 0.7126)$ and $(x_1, x_2) = (0.0898, -0.726)$. The global minimum value is -1.0316.

Goldstein-price f unction:

$$h(x_1,x_2)=[1+(x_1+x_2+1)^2\cdot(19-14x_1+3x_1^2-14x_2+6x_1x_2+3x_2^2)]$$

$$r(x_1,x_2)=[30+(2x_1-3x_2)^2\cdot(18-32x_1+12x_1^2+48x_2-36x_1x_2+27x_2^2)]$$

$$f_8=h(x_1,x_2)\cdot r(x_1,x_2)$$

where, $-2\le x_1, x_2\le 2$.

This function has a global minimum value 3 at point $(x_1, x_2) = (0, -1)$.

Eazom function:

$$f_9=-\cos(x_1)\cdot\cos(x_2)\cdot\exp(-(x_1-\pi)^2-(x_2-\pi)^2)$$

where, $-100\le x_1, x_2\le 100$

This function has a global minimum value -1 at point $(x_1, x_2) = (\pi, \pi)$.

Shubert function:

$$f_{10}=\sum_{i=1}^{5} i\cdot\cos[(i+1)\cdot x_1+i]\cdot\sum_{i=1}^{5} i\cdot\cos[(i+1)\cdot x_2+i]$$

where, $-10\le x_1, x_2\le 10$

This function has a global minimum value -186.7309 at 18 points.

When UOP-KEA was used to search the optimal minimum for function f_1~f_{10}, the parameters were set in Table 1, in which n denotes the number of variable dimension, obj * ()denotes the known optimal values of functions, T denotes the biggest number of evolution generation, G denotes the size of knowledge base and M denotes the scale of evolution.

Experiments were done repeatedly 50 times for each objective function. The test results were shown in Table 2, in which obj_{AV} () denotes the average optimal value of 50 times optimization, T_{AV} denotes the average convergence generation of 50 times optimization and R_{CONV} denotes the global convergence rate.

RESULTS ANALYSIS

The test experiment includes three parts:

- The optimal value of objective functions
- The convergence generation number
- The global convergence rate

Three parts are designed to prove the optimization performance for the above test functions.

From Table 2, we can see: (1) the success rate of UOP-KEA for 10 test functions is all 100%. The average optimization optimal values of 50 times are basically the same as the objective optimal value. It is shown that the algorithm has a good global convergence and (2), for both high-dimensional function and low-dimensional function, the algorithm can converge with a less number of average generations. The maximal average generation number is 195.2 and the minimal average generation number is only 28.0. So, the convergence speed of this algorithm is satisfactory. The above results show that UOP-KEA has a good optimization performance for the unconstraint nonlinear test functions.

CONCLUSION

An algorithm for solving unconstraint optimization problems utilizing knowledge evolution principle (UOP-KEA) was proposed in this study. It provides an algorithm framework for solving the unconstraint optimization problems. Successful results were gained when experiments were taken on optimization of unconstraint nonlinear test functions utilizing this algorithm. The global optimal solutions could be found by this algorithm with a smaller population and a less number of iterations. So, the algorithm has a good optimization performance. The main future work is to prove the global convergence of the algorithm theoretically and evaluate its performance. Furthermore, this algorithm should be integrated widely with other kinds of traditional evolutionary algorithms in order to broaden its applications.

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REFERENCES

Bert, T., 2009. Training the rivers and exploring the coasts. Knowledge evolution in the Netherlands in two engineering fields between 1800 and 1940. Phys. Chem. Earth, 34: 132-141.

Bowonder, B. and T. Miyake, 2000. Technology strategy of Toshiba Corporation: A knowledge evolution perspective. Int. J. Technol. Manage., 19: 864-895.

Deborah, W.M., 2003. A teachnical report of cost-benefit analysis of confidentiality policies for advanced knowledge management systems. Report No. UCRL-ID-152211. https://e-reports-ext.llnl.gov/pdf/243861.pdf.

Fikret, B., 2009. Evolution of co-management: Role of knowledge generation, bridging organizations and social learning. J. Environ. Manage., 90: 1692-1702.

Fu, J., C. Zhou and G. Jiang, 2005. Hypothesis and Contradiction: Increasing of Science Knowledge. 1st Edn., Shanghai Translation Publishing Co., Shanghai.

Huang, H., X. Gu and M. Liu, 2007. Research on cultural algorithm for solving nonlinear constrained optimization. Acta Automatica Sinica, 33: 1115-1120.

Li, M., J. Kou, D. Lin and S. Li, 2002. Basic Principle and Application of Genetic Algorithm. 1st Edn., Science Publishing Co., Beijing.

Liu, C., S. Yang and Y. Zhang, 2007. Knowledge evolution strategy. Syst. Eng. Electronics, 29: 1017-1020.

Menicucci, D.F., 2006. A knowledge continuity management program for the energy, infrastructure and knowledge systems center, Sandia National Laboratories. Report No. SAND2006-4061. http://prod.sandia.gov/techlib/access-control.cgi/2006/064061.pdf.

Shu, W. and R. Zuo, 2005. Impersonal Knowledge: Research on A Evolutionism. 1st Edn., Shanghai Translation Publishing Co., Shanghai.

Thomas, M., 2009. Human knowledge, rules and the spontaneous evolution of society in the social thought of Darwin, Hayek and Boulding. J. Econ. Behav. Org., 71: 62-74.

Wang, X. and L. Cao, 2002. Genetic Algorithm, Theory, Application and Software Realization. 1st Edn., Xian Jiao Tong University Press, Xian.

Xu, Z. and N. Zhao, 2006. Factors, form and law of knowledge evolution. J. Xichang Coll., 18: 95-97.

Zhong, Y., 2007. Knowledge concepts and measures in views of Information-Knowledge-Intelligence eco-system. J. Frontiers Comput. Sci. Technol., 1: 129-137.

Zhou, M. and S. Sun, 1999. Principle and Application of Genetic Algorithm. 1st Edn., National Defence Industry Publishing Co., Beijing.

Zhu, Z., 2000. Research on the mechanism of knowledge evolution and knowledge innovation. Management, 12: 16-19.