Journal of Southeast University (English Edition) Vol. 28, No. 2, pp. 145 - 150 June 2012 ISSN 1003—7985

Adaptive multicascade attribute reduction based on quantum-inspired mixed co-evolution

Ding Weiping[1,2] Wang Jiandong[1] Shi Quan[2] Guan Zhijin[2]

([1] College of Computer Science and Technology, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China)
([2] School of Computer Science and Technology, Nantong University, Nantong 226019, China)

Abstract: Due to the fact that conventional heuristic attribute reduction algorithms are poor in running efficiency and difficult in accomplishing the co-evolutionary reduction mechanism in the decision table, an adaptive multicascade attribute reduction algorithm based on quantum-inspired mixed co-evolution is proposed. First, a novel and efficient self-adaptive quantum rotation angle strategy is designed to direct the participating populations to mutual adaptive evolution and to accelerate convergence speed. Then, a multicascade model of cooperative and competitive mixed co-evolution is adopted to decompose the evolutionary attribute species into subpopulations according to their historical performance records, which can increase the diversity of subpopulations and select some elitist individuals so as to strengthen the sharing ability of their searching experience. So the global optimization reduction set can be obtained quickly. The experimental results show that, compared with the existing algorithms, the proposed algorithm can achieve a higher performance for attribute reduction, and it can be considered as a more competitive heuristic algorithm on the efficiency and accuracy of minimum attribute reduction.

Key words: attribute reduction; mixed co-evolution; self-adaptive quantum rotation angle; performance experience record; elitist competition pool

doi: 10.3969/j.issn.1003 - 7985.2012.02.003

Rough set theory is a valid mathematic tool to handle imprecision, uncertainty and vagueness. Attribute reduction in rough set theory has been recognized as an important approach for feature selection and knowledge discovery[1]. It helps us to find the minimum attribute set and induce the minimum length of decision rules in an information system. However, the problem of finding a minimum reduction is more difficult and it has been proven to be an NP-hard problem by Wong and Ziarko[2]. Due to the fact that traditional algorithms often fail to find optimal solutions, many research efforts have shifted to evolutionary algorithms (EA) to find near-optimal solutions, such as the genetic algorithm (GA)[3], ant colony optimization (ACO)[4], and particle swarm optimization (PSO)[5], etc. These algorithms can often obtain high quality solutions, but each performance deteriorates rapidly when the dimensionality of the search space increases so that thousands of seconds may be required. Till now, they are not quite effective in the sense that the probability for them to find a minimum attribute reduction in a large information system appears to be lower.

The co-evolution, inspired by the reciprocal evolutionary change of the cooperative or competitive interaction between different species, has recently been a hot research topic of computational intelligence. Several studies have shown that the introduction of ecological models and co-evolutionary architectures represent a significant improvement over conventional evolutionary algorithms[6]. The co-evolutionary algorithms can be generally classified into two main categories: competitive co-evolution and cooperative co-evolutionary algorithm. For the competitive co-evolutionary algorithm, various subpopulations will always fight to gain an advantage over the others. However, for the cooperative co-evolutionary algorithm , subpopulations will exchange information within each other during the evolutionary process. Both the competitive co-evolutionary algorithm and the cooperative co-evolutionary algorithm have their unique advantages for maintaining diversity in the species, and they have successfully been applied in many large difficult optimization problems [7-9].

During the practical process of attribute reduction, there are some interacting attribute subsets which may not be decomposed in one subpopulation because there is almost no prior information about how the attribute subsets interact. It turns out that there would be a major decline in the overall performance of traditional co-evolutionary algorithms when these interacting attribute subsets are decomposed in different subpopulations. Thus arises the need for more sophisticated co-evolutionary algorithms capable of capturing the interacting attribute subsets and

Received 2011-10-11.

Biographies: Ding Weiping (1979—), male, graduate, lecturer, ding_wp@nuaa.edu.cn; Wang Jiandong (1945—), male, professor, aics@nuaa.edu.cn.

Foundation items: The National Natural Science Foundation of China (No. 61139002, 61171132), the Funding of Jiangsu Innovation Program for Graduate Education (No. CXZZ11_0219), the Natural Science Foundation of Jiangsu Province (No. BK2010280), the Open Project of Jiangsu Provincial Key Laboratory of Computer Information Processing Technology (No. KJS1023), the Applying Study Foundation of Nantong (No. BK2011062).

Citation: Ding Weiping, Wang Jiandong, Shi Quan, et al. Adaptive multicascade attribute reduction based on quantum-inspired mixed co-evolution[J]. Journal of Southeast University (English Edition), 2012, 28(2): 145 - 150. [doi: 10.3969/j.issn.1003 - 7985.2012.02.003]

decomposing them in the same subpopulation. So this will be extended to better performance in the competitive solution for minimum attribute reduction.

As a novel evolutionary algorithm, the quantum-inspired evolutionary algorithm was proposed by Han and Kim[10], in which the Q-bit individual has a better characteristic of population diversity than any other representative. Meanwhile, the quantum rotation gate is used as the update mechanism, which can guide the searching direction into the optimal area and accelerate the algorithm's convergence speed. As for considering the superiorities of the quantum-inspired evolutionary algorithm and the cooperative and competitive co-evolutionary algorithm, we combine them to put forward a novel adaptive multicascade attribute reduction algorithm (QMCAM_AR) based on quantum-inspired mixed co-evolution. The adaptive quantum rotation angle strategy and the cooperative and competitive mixed co-evolutionary multicascade model are adopted to find the global optimization solution of attribute reduction quickly. Experimental results demonstrate that the proposed algorithm achieves a promising performance for minimum attribute reduction, and it is better in feasibility and effectiveness than other algorithms.

1 Minimum Attribute Reduction Model

Let $I = (U, A)$ be an information system, where U, called universe, is a nonempty set of finite objects; A is a nonempty finite set of attributes such that a: $U \to V_a$ for every $a \in A$; V_a is the value set of a. In a decision system, $A = C \cup D$ where C is the set of condition attributes and D is the set of decision attributes.

Definition 1 Given an arbitrary set $x \subseteq U$, the P-lower approximation of X, denoted as $\underline{P}X$, is the set of all elements of U, which can be certainly classified as elements of X based on the attribute set P. The definition is expressed as

$$\underline{P}X = \{x \mid [x]_P \in X\} \tag{1}$$

The P-upper approximation of X, denoted as $\overline{P}X$, is the set of all elements of U, which can be possibly classified as elements of X based on the attribute set P. The definition can be also expressed as

$$\overline{P}X = \{x \mid [x]_P \cap X \neq \varnothing\} \tag{2}$$

Definition 2 Let P, $Q \subseteq A$, it is said that Q depends on P in a dependency degree $k(0 \leqslant k \leqslant 1)$, denoted $P \Rightarrow_k Q$, if

$$k = \gamma_P(Q) = \frac{\mid \mathrm{POS}_P(Q) \mid}{\mid U \mid} \tag{3}$$

where $\mid \cdot \mid$ is the cardinality of a set. $\mid \mathrm{POS}_P(Q) \mid$, called positive region, is defined by

$$\mid \mathrm{POS}_P(Q) \mid = \bigcup_{X \in U/Q} \underline{P}X \tag{4}$$

The positive region contains all the objects in U that can be uniquely classified into blocks of the partition U/Q by means of the knowledge of attributes P. The quantity k can be used to measure the degree of dependency between Q and P.

Definition 3 During the attribute reduction, the irrelevant attributes can be removed from the original attribute set and the remaining attributes can keep the discriminability as the same as the original attribute set. Let R be a subset of C, and then R is said to be a reduction if

$$\mathrm{RED} = \{R \subseteq C \mid \gamma_R(D) = \gamma_C(D),\ \forall B \subset R, \gamma_B(D) \neq \gamma_C(D)\} \tag{5}$$

A reduction with minimal cardinality is called a minimum reduction, and it can be written as

$$\mathrm{RED}_{\min} = \{R \in \mathrm{RED} \mid \forall R' \in \mathrm{RED},\ \mid R \mid \leqslant \mid R' \mid\} \tag{6}$$

Minimum attribute reduction can be formulated as a nonlinearly constrained combinatorial optimization problem as follows:

$$\begin{aligned} F(x) &= \min \mid R \mid \\ \text{s. t.} \quad & R \subseteq C \\ & \gamma_R(D) = \gamma_C(D) \\ & \forall q \in R,\ \gamma_{R \setminus \{q\}}(D) = \gamma_R(D) \end{aligned} \tag{7}$$

2 Adaptive Multicascade Attribute Reduction Algorithm

2.1 Fitness function of attribute reduction

In the QMCAM_AR algorithm, the fitness function considers both the size of the attribute subset and its evaluated suitability. It will be changed with the evolutionary process of attribute reduction and it can be calculated as

$$\mathrm{Fitness}(x) = \alpha \gamma_R(D) \frac{\gamma_{\xi(x)}(D)}{\gamma_C(D)} + (1-\alpha) \frac{\mid C(x) \mid - \mid R(x) \mid}{\mid C(x) \mid} \frac{\mathrm{Core}(\xi(x))}{\gamma_{\xi(x)}(D)} \tag{8}$$

where $\gamma_R(D)$ is the classification quality of condition attributes R relative to decision attributes D; $\mid C(x) \mid$ is the total number of attribute features; $\mid R(x) \mid$ is the number of "1" in a coded position or the length of the selected attribute subsets; $\xi(x)$ is the attribute subsets; Core $(\xi(x))$ is the reduction core of the attribute subsets, and $\alpha(\alpha \in [0, 1])$ is the parameter corresponding to the importance of the classification quality and the subset length.

2.2 Self-adaptive quantum rotation angle

In order to automatically update the rotation gate, adjust the subpopulation size and accelerate the convergence speed, we give a novel strategy of the adaptive quantum rotation angle among mutual co-evolutionary subpopulations.

A quantum angle is defined as an arbitrary angle θ and a Q-bit is presented as $[\theta]$. $[\theta]$ is equivalent to the original Q-bit as $\begin{bmatrix} \sin(\theta) \\ \cos(\theta) \end{bmatrix}$, and it satisfies that $|\sin(\theta)|^2 + |\cos(\theta)|^2 = 1$ spontaneously. Then the m Q-bit $\left[\begin{array}{c|c|c|c|} \alpha_1 & \alpha_2 & \alpha_3 & \dots\ \alpha_m \\ \beta_1 & \beta_2 & \beta_3 & \dots\ \beta_m \end{array}\right]$ can be replaced by $[\theta_1 | \theta_2 | \theta_3 | \dots | \theta_m |]$. The rotation gate is replaced as

$$\theta_i = s(\alpha_i, \beta_i)\Delta\theta \tag{9}$$

where $s(\alpha_i, \beta_i)$ is the rotation sign of θ_i, which can determine the direction, and $\Delta\theta$ is the magnitude of the rotation angle. The lookup table mechanism, adopted in the traditional selection of the rotation angle, will cause the evolutionary algorithms to be prematurely convergent and fall into a local optimum inefficiently[11]. In this paper, a novel and efficient self-adaptive quantum rotation angle is designed. The angle distance between Q-bit ($|\varphi\rangle$, $|\varphi'\rangle$) is shown in Fig. 1 and it is formulated as

$$\Delta\theta_{i\,|\varphi\rangle,\varphi'\rangle} = \arctan\left(\frac{\alpha'}{\beta'}\right) - \arctan\left(\frac{\alpha}{\beta}\right)$$
$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle, \quad |\varphi'\rangle = \alpha'|0\rangle + \beta'|1\rangle \tag{10}$$

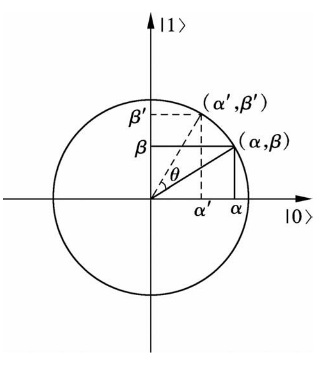

Fig. 1 Angle distance between $|\varphi\rangle$ and $|\varphi'\rangle$

The self-adaptive quantum rotation angle θ_i is defined as

$$\theta_i = \left(1 - \frac{\theta'_{\rm b} - \theta'_{\rm w}}{\theta_{\rm b} - \theta_{\rm w}}\right)^m \Delta\theta_{i\,|\varphi\rangle,*} \tag{11}$$

where $\Delta\theta_{i|\varphi\rangle,*}$ is the angle-distance between the i-th Q-bit and the basic state; $\theta'_{\rm b}$ represents the global best fitness solution in all the co-evolutionary subpopulations; $\theta'_{\rm w}$ is the corresponding global worst fitness; $\theta_{\rm b}$ is the local best fitness individual in a decomposed subpopulation; $\theta_{\rm w}$ is the corresponding local worst fitness individual; and m is the number of iterations. The self-adaptive adjusting steps of the quantum rotation angle are updated as follows.

Algorithm 1 The main adaptive adjusting steps of the quantum rotation angle

1) If $((f(b) \geqslant f(x)) \wedge (b_i = 0) \wedge (x_i = 1))$

//x_i is the i-th Q-bit of the current chromosome, and b_i is the i-th Q-bit of the object;

//$f(x)$ is the fitness of x_i, and $f(b)$ is the fitness of b_i.

$$\Delta\theta_{i\,|\varphi\rangle,*} = \Delta\theta_{i\,|\varphi\rangle,|0\rangle} = -\arctan\frac{\alpha_i}{\beta_i};$$

$$\theta_i = -\left(1 - \frac{\theta'_{\rm b} - \theta'_{\rm w}}{\theta_{\rm b} - \theta_{\rm w}}\right)^m \arctan\frac{\alpha_i}{\beta_i}.$$

2) Else if $((f(b) \geqslant f(x)) \wedge (b_i = 1) \wedge (x_i = 0))$

$$\Delta\theta_{i|\varphi\rangle,*} = \Delta\theta_{i|\varphi\rangle,|1\rangle} = \frac{\pi}{2} - \arctan\frac{\alpha_i}{\beta_i};$$

$$\theta_i = \left(\frac{\pi}{2} - \left(1 - \frac{\theta'_{\rm b} - \theta'_{\rm w}}{\theta_{\rm b} - \theta_{\rm w}}\right)^m\right)\arctan\frac{\alpha_i}{\beta_i}.$$

3) Else $\Delta\theta_{i\,|\varphi\rangle,*} = 0$ and $\theta_i = 0$.

2.3 Cooperative and competitive mixed co-evolutionary model

In the QMCAM_AR algorithm, a cooperative and competitive mixed co-evolutionary model for attribute reduction is adopted to decompose the evolutionary attributes. The cooperation process mainly includes the discovery of interdependent attribute subsets within the same species and their reasonable decompositions. Since the shuffled frog-leaping algorithm (SFLA), which is a combination of the genetic-based memetic algorithm and the social behavior-based particle swarm optimization algorithm, has the efficient mathematical function and global search capability[12], we choose it as the subpopulation optimizer. And the competitive process, in which the global best or worst subpopulation and the local best or worst individuals are all selected out, will trigger a potential race in two kinds of competitive pools so as to improve their respective contributions to the overall fitness. The main steps of cooperative and competitive mixed co-evolution are as follows.

Algorithm 2 The main steps of cooperative and competitive mixed co-evolution

1) Decompose the population S into n subpopulations S_i based on the performance experience record R_i (R_i is set to 1 initially), namely $S = \sum_{i=1}^{n} S_i$, and initialize $S_{i,j}$ as the j-th individual of the subpopulation S_i.

2) For each S_i do

Create the i-th competition pool P_i for the subpopulation S_i.

For $j = 1$ to $|S_i|$ do

Assign Pareto rank to $S_{i,j}$ and calculate niche count of $S_{i,j}$;

Evaluate the fitness of $S_{i,j}$ and compare with the competition fitness of its brother individual by the roulette wheel.

Select D_i as the best fitness individual representative for the current subpopulation S_i.

Construct the elitist performance experience record R_i, and it is updated according to $R_i = \left|\frac{f_{\rm b} - f_{\rm w}}{f_{\rm b}}\right|$, where $f_{\rm b}$ is the best fitness and f_w is the worst one of the subpopulation.

Optimize the subpopulation S_i separately with SFLA in its respective P_i for a predefined number of fitness evaluations.

3) Create the elitist competition pool P_e for representing the whole population.

4) Insert all the elitist individuals $D = \{D_1, \ldots, D_n\}$ into P_e with the performance experience record list $R = \{R_1, \ldots, R_n\}$.

5) Shuffle all the elitist individuals and evaluate each D_i by combining with other brother elitist individuals.

6) Determine the winning global elitist individual D_e and its corresponding subpopulation S_e.

7) Decompose the population S based on R, and go to 2) to form the multicascade model until the stopping criterion is met.

2.4 Main processes of the QMCAM_AR algorithm

Based on the self-adaptive quantum rotation angle and the cooperative and competitive mixed co-evolutionary model, we put forward an adaptive multicascade attribute reduction algorithm. Its main key steps are described as follows:

Algorithm 3 Key steps of the QMCAM_AR algorithm

1) Create n subpopulations based on the historical performance experience records R, where the i-th sub-population S_i represents the i-th condition attribute subset AS_i. Represent each co-evolutionary subpopulation position as binary bit strings of length N, where N is the total number of attribute subsets. Each bit denotes an attribute, in which "1" means the corresponding attribute is selected, while "0" means not selected. Each position string is to optimize an attribute subset.

2) Let $\{0,1\}^m$ be the m-dimensional Boolean space and ξ be a mapping from $\{0,1\}^m$ to the power set 2^C as $x_i = 1 \Leftrightarrow a_i \in \xi(x)$, $a_i \in C$, $i = 1, 2, \ldots, m$.

3) Eq. (7) can be refined as the following constrained binary optimization object:

$$\begin{aligned} & F(x) = \min(S(x)) \\ \text{s.t.}\quad & x \in \{0,1\}^m,\ \gamma_{\xi(x)}(D) = \gamma_C(D) \\ & \forall q \in \xi(x),\ \gamma_{\xi(x)\setminus\{q\}}(D) = \gamma_{\xi(x)}(D) \end{aligned}$$

4) Use multistate quantum bits to encode $Q(t) = \{q_1^t, q_2^t, \ldots, q_n^t\}$, $q_j^t = [\theta_{j1}^t \mid \theta_{j2}^t \mid \ldots \mid \theta_{jm}^t]$, and encode the position of the elitist subpopulation S_e into a potential subsolution of the attribute reduction.

5) Do {Select ($AS_i \subseteq C$)

Activate the cooperative and competitive multicascade model according to Algorithm 2.

Optimize attribute subset AS_i by subpopulation S_i.

Calculate $\gamma_{\xi(x)}(D)$ and collaborate to form the complete solution.

} While $\gamma_{\xi(x)}(D) = \gamma_C(D)$.

6) Update the quantum rotation angle of subpopulation S_i representative of attribute subset AS_i according to Algorithm 1, and mutate them by the predefined probability P_m.

7) Calculate the fitness of the global elitist individuals D_e in S_e so as to determine the attribute subset RED and RED_{min}, and then renew the experience record list R.

8) Stop if the halting criterion is not satisfied; otherwise go to 5) for the next iteration.

9) Output the minimal reduction set RED_{min} for the global attribute optimization.

3 Evaluation Experiments

Several experiments are conducted to evaluate the performance of the QMCAM_AR algorithm. And we compare it with the representative algorithms, namely CCQGA[8], CCPSO[13], HEA[14]. These algorithms are encoded with Visual C++6.0 and implemented on a 2.8 GHz machine running Windows XP with 1 024 MB of main memory. The relative parameters of the compared algorithms are the same with their respective references. They are tested on Benchmark functions provided by CEC'2008 special session on large scale global optimization[15]. Functions f_1 and f_4 are separable, and functions f_2 and f_3 are completely nonseparable where interaction exists between any two variables. Experiments of these functions are conducted on 800-D. The maximal fitness evaluation number is set to 5×10^5. Here the four algorithms are all terminated after 1 000 iterations. The parameter α is set to 0.4, and P_m is 0.25. All the results are averaged over 10 independent runs and the average fitness values are given in Tab. 1.

It can be found that QMCAM_AR has better performance on the tested set than the other algorithms. Especially for the nonseparable functions f_2 and f_3, it can pursue better near-optimization by self-adaptive decomposition, and achieve some significant results by avoiding premature convergence and local optimization efficiently.

Ten UCI machine learning datasets[16] are taken to test the attribute reduction ability of QMCAM_AR. Tab. 2 describes the experimental results of average iterations and runtime to obtain the minimal attribute reduction. Except for Monks and Breast Cancer datasets, the global minimal

Tab. 1 Experimental results with 800-D on test functions f_1 to f_4

Function	CCQGA	CCPSO	HEA	QMCAM_AR
f_1	2.3345×10^{-11}	6.9081×10^{-12}	1.0064×10^{-11}	2.5608×10^{-12}
f_2	6.8978×10^{2}	4.3398×10^{3}	2.2376×10^{3}	1.3209×10^{2}
f_3	4.4350×10^{4}	1.0978×10^{3}	2.7803×10^{4}	3.9701×10^{2}
f_4	3.5603×10^{-9}	6.1703×10^{-10}	4.3766×10^{-8}	1.2114×10^{-10}

attribute reduction can be found in less than 60 iterations. Even for Monks and Breast Cancer, QMCAM_AR also can find the minimal attribute reduction within 18 s.

Tab. 2 Average iterations and runtime to obtain the minimal attribute reduction

Dataset	Number of attribute	Average iterations	Average runtime/s
Zoo	43	39	0.89
Heart	23	19	1.12
Lung	46	35	0.73
Sonar	68	29	2.02
Exactly2	32	30	0.83
Letters	53	43	1.59
Monks	209	162	15.12
Mushroom	67	56	1.64
Ionosphere	37	49	1.01
Breast Cancer	323	234	17.23

In addition, we compare QMCAM_AR with two other attribute reduction and feature selection algorithms, namely PSORSFS[17] and IDSRSFS[18], on attribute reduction error rates when different minimal reduction sets are obtained. We test three algorithms on the Tic-tac-toe dataset and the Soybean dataset. Each algorithm is independently run 10 times, and the average error rate curves are shown in Fig. 2.

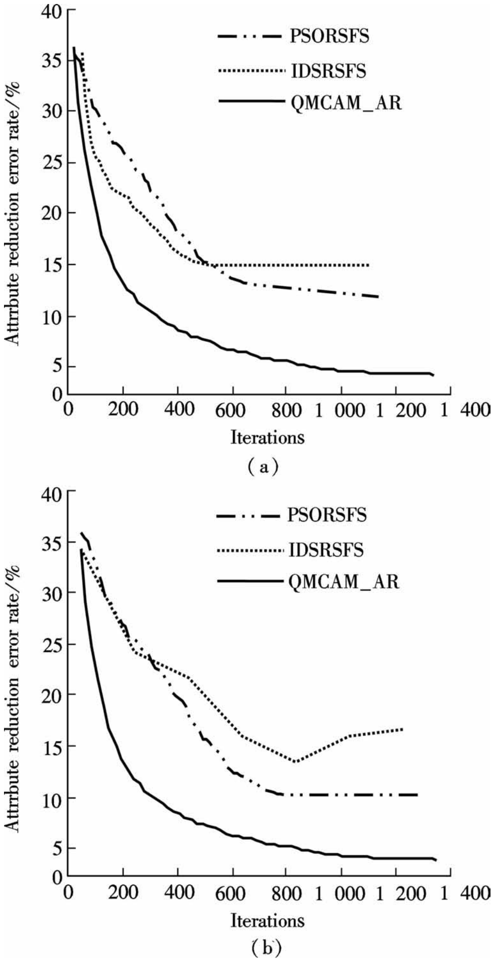

Fig. 2 Comparison of error rates. (a) Tic-tac-toe; (b) Soybean

Obviously, the QMCAM_AR outperforms the PSORSFS and the IDSRSFS on the tested datasets and it usually uses only very few iteration numbers to obtain the minimal attribute reduction error rate. Since the QMCAM_AR uses the self-adaptive quantum rotation angle to accelerate the convergence speed and the cooperative and competitive mixed co-evolutionary multicascade model to adjust the attribute subsets size and to balance exploration and exploitation, it has a higher accuracy probability of obtaining a minimum attribute reduction in the limited iterations.

The above experimental results indicate that the QMCAM_AR can obtain a better solution set in effectiveness and efficiency. So it is a more competitive algorithm for minimum attribute reduction.

4 Conclusion

In this paper, we put forward a novel adaptive multicascade attribute reduction algorithm based on quantum-inspired cooperative and competitive mixed co-evolution. The innovation of our research is to propose two new strategies to find a global optimization solution of attribute reduction. First, a novel mechanism of the self-adaptive quantum rotation angle can accelerate the convergence speed. Secondly, the cooperative and competitive mixed co-evolutionary multicascade model can decompose the evolutionary attribute species into subpopulations according to the historical performance experience records and it can accelerate to obtain a global optimization reduction set so as to strengthen the sharing ability of the elitists' searching experience. Experimental results demonstrate that the proposed algorithm remarkably outperforms some existing algorithms and it has better feasibility and effectiveness in finding the minimum attribute reduction.

References

[1] Pawlak Z. Rough sets[J]. *International Journal of Computer and Information Sciences*, 1982, **11**(5): 341 −356.

[2] Wong S K M, Ziarko W. On optimal decision rules in decision tables[J]. *Bulletin of Polish Academy of Science*, 1985, **33**(11): 693 −696.

[3] Slezak D, Wroblewski J. Order based genetic algorithms for the search of approximate entropy reducts[C]//*The 9th International Conference on Rough Sets, Fuzzy Sets, Data Mining and Granular Computing*. Chongqing, China, 2003: 308 −311.

[4] Jensen R, Shen Q. Finding rough set reducts with ant colony optimization[C]//*Proceedings of the 2003 UK Workshop on Computational Intelligence*. Bristol, UK, 2003: 15 −22.

[5] Wang X Y, Yang J, Teng X, et al. Feature selection based on rough sets and particle swarm optimization[J]. *Pattern Recognition Letters*, 2007, **28**(4): 459 −471.

[6] Potter M. The design and analysis of a computational model of cooperative co-evolution [D]. Fairfax, VA,

USA: George Mason University, 1997.

[7] Chen H Y, Wang X F. Cooperative co-evolutionary algorithm for unit commitment[J]. *IEEE Transactions on Power Systems*, 2002, **17**(1): 128-133.

[8] Gu Jinwei, Gu Manzhan, Cao Cuiwen, et al. A novel competitive co-evolutionary quantum genetic algorithm for stochastic job shop scheduling problem[J]. *Computers & Operations Research*, 2010, **37**(5): 927-937.

[9] Omidvar Mohammad Nabi, Li Xiaodong, Yao Xin. Cooperative co-evolution with delta grouping for large scale non-separable function optimization [C]//2010 *IEEE World Congress on Computational Intelligence*. Barcelona, Spain, 2010: 1762-1769.

[10] Han K H, Kim J H. Quantum-inspired evolutionary algorithms with a new termination criterion, gate, and two-phase scheme[J]. *IEEE Transactions on Evolutionary Computation*, 2004, **8**(2): 156-169.

[11] Zhang Gexiang. Quantum-inspired evolutionary algorithms: a survey and empirical study[J]. *Journal of Heuristics*, 2011, **17**(3): 303-335.

[12] Amiri B, Fathian M, Maroosi A. Application of shuffled frog-leaping algorithm on clustering [J]. *The International Journal of Advanced Manufacturing Technology*, 2009, **45**(1/2): 199-209.

[13] Goh C K, Tan K C, Liu D S, et al. A competitive and cooperative co-evolutionary approach to multi-objective particle swarm optimization algorithm design[J]. *European Journal of Operational Research*, 2010, **202**(1): 42-54.

[14] Wu Shelly X, Banzhaf Wolfgang. A hierarchical cooperative evolutionary algorithm[C]//*Proceedings of the 12th Annual Conference on Genetic and Evolutionary Computation*. Portland, Oregon, USA, 2010: 233-240.

[15] Tang K, Yao X, Suganthan P N, et al. Benchmark functions for the CEC'2008 special session and competition on large scale global optimization [R]. Hefei, China: Nature Inspired Computation and Applications Laboratory, University of Science and Technology of China, 2007.

[16] Asuncion A, Newman D J. UCI repository of machine learning databases [EB/OL]. (2007-06) [2011-10-06]. http://www.ics.uci.edu/~mlearn/mlrepository.

[17] Wang X, Yang J, Jensen R, et al. Rough set feature selection and rule induction for prediction of malignancy degree in brain glioma computer methods and programs in biomedicine[J]. *Computer Methods and Programs in Biomedicine*, 2006, **83**(2): 147-156.

[18] Bae Changseok, Yeh Wei-Chang, Chu Yuk Ying, et al. Feature selection with Intelligent dynamic swarm and rough set[J]. *Expert Systems with Applications*, 2010, **37**(10): 7026-7032.

基于量子混合协同进化的自适应多级联属性约简

丁卫平[1,2]　王建东[1]　施　佺[2]　管致锦[2]

([1]南京航空航天大学计算机科学与技术学院，南京 210016)

([2] 南通大学计算机科学与技术学院，南通 226019)

摘要:针对传统生物启发式方法在决策表中属性约简求解效率不高和难以协同约简等问题,提出一种基于量子混合协同进化的自适应多级联属性约简算法.首先设计了一种新型高效的自适应量子角旋转策略,指导参与属性约简的进化种群自适应相互演进,加速算法收敛.然后构建了合作和竞争混合的协同进化级联模型,根据执行经验记录分割属性种群集,提高约简子种群的多样性,并产生种群精英以增强其寻优经验共享,快速找到全局最小属性约简集.实验结果表明,与同类典型算法相比,该算法在最小属性约简效率和精度方面具有明显优势.

关键词:属性约简;混合协同进化;自适应量子旋转角;执行经验记录;精英竞争池

中图分类号:TP301.6