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A novel approach to minimum attribute reduction based on quantum-inspired self-adaptive cooperative co-evolution

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ABSTRACT

Attribute reduction in rough set theory is an important feature selection method. However it has been proven as an NP-hard problem to find minimum attribute reduction. It is therefore necessary to investigate efficient heuristic algorithms to find near-optimal solutions. In this paper, a novel and efficient minimum attribute reduction algorithm based on quantum-inspired self-adaptive cooperative co-evolution incorporated into shuffled frog leaping algorithm is proposed. First, evolutionary frog individuals are represented by multi-state quantum bits, and self-adaptive quantum rotation angle and quantum mutation probability strategy are adopted to update the operation of quantum revolving door. Second, a self-adaptive cooperative co-evolutionary model for minimum attribute reduction is designed to divide the evolutionary attribute sets into reasonable subsets. The subsets are assigned the self-adaptive mechanism according to their historical performance records, and each of them is evolved by the quantum-inspired shuffled frog leaping algorithm. So the reasonable decompositions are more easily produced by exploiting any correlation and interdependency between attribute subsets interaction. Finally, global convergence of the proposed algorithm is proved in theory, and its performance is investigated on some global optimization functions, UCI datasets and magnetic resonance images (MRIs), compared with existing state-of-the-art algorithms. The results demonstrate that the proposed algorithm can achieve a higher performance on the convergence rate and stability of attribute reduction. So it can be considered as a more competitive heuristic algorithm on the efficiency and accuracy of minimum attribute reduction.

1. Introduction

Rough set theory proposed by Pawlak in [1] is a new mathematic tool to analyze imprecision, uncertainty and vagueness. In recent years, it has gained the considerable importance and is applied in diversified research areas, especially in data mining, knowledge discovery, artificial intelligence, and information systems analysis [2–6]. Attribute reduction is one of the most important topics of rough set theory, which helps us to find out the minimum attribute sets and induce minimal length of decision rules inherent in an information system. So a fast and efficient attribute reduction algorithm is especially important for implementing the attribute reduction in data mining and knowledge discovery applications with huge data sets.

Finding one reduction is not so difficult and there have been many algorithms available in the literatures [7–16] for this purpose, while, finding a minimum reduction set is more difficult and it has been proven to be an NP-hard problem by Wong and Ziarko [17]. Evolutionary algorithms (EAs) and other meta-heuristics have shown to be powerful in solving a wide range of global optimization problems. So the high complexity of minimum attribute reduction has motivated a few investigators to apply EAs to finding out near-optimal solutions. For instance:

a. Slezak and Wroblewski [18] and Banerjee et al. [19] discussed the application of genetic algorithm (GA) to the minimum attribute reduction in different ways.
b. Jensen and Shen [20] and Ke et al. [21] introduced the ant colony optimization (ACO) approach to the attribute reduction. Some results in their research were reported.
c. Wang et al. [22] and Ye et al. [23] applied the particle swarm optimization (PSO) to this problem and provided some competitive solutions.
d. Bae et al. [24] also proposed an intelligent dynamic swarm (IDS) optimization, a modified PSO, and applied it to attribute reduction as to select features from huge data sets and find the optimum reduction set in limited iteration times.

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Although these algorithms can usually yield good solutions, they are still time-consuming to compute and their performances deteriorate rapidly as the increasing complexity and dimensionality of the search space. Moreover, there are many interacting decision variables which exist in different attribute subsets during the practical process of attribute reduction. Due to seldom prior information about how attribute decision variables are interacting, these interacting decision variables are usually placed in different populations. As a result, the overall performance of these algorithms would decline. So far, these algorithms [18–24] are not quite effective, as it is less possible to find minimum attribute reduction in the large information system. Some new techniques need to be extended to better performances in terms of solution quality and competitive computation complexity for attribute reduction.

The co-evolution, inspired by the reciprocal evolutionary change and driven by the cooperative or competitive interaction between different species, has been a hot research topic of computational intelligence recently [34]. Several studies [25–35] have shown the introduction of ecological models and co-evolutionary architectures is the significant improvement over conventional EAs. Co-evolution can be classified into two groups, namely, competitive co-evolution and cooperative co-evolution. While the former tries to make individuals more competitive through evolution, the latter aims to find from which systems individuals can be better constructed [29]. Several other studies [31–35] have shown that co-evolutionary frameworks increase the efficiency of traditional EAs. The cooperative co-evolutionary (CC) algorithm proposed by Potter and De Jong [25] is a framework for decomposing of a n-dimensional decision vector into n subcomponents, each of which can be optimized with a separate evolutionary algorithm. The fitness of an individual depends on its ability to collaborate with individuals from other species. Potter and De Jong firstly incorporated CC into GA called cooperative co-evolutionary GA (CCGA), and showed the significant improvement over traditional GA [26]. But CCGA converged prematurely for the non-separable functions where a proportion of decision variables interact with each other. Bergh and Engelbrecht [29] applied CC to PSO, called cooperative PSO (CPSO), and they divided a n-dimensional problem into m s-dimensional subcomponents. Every individual in a subcomponent was evaluated by concatenating the individual with the best-fit in the rest of the subcomponents to form a context vector. One major drawback of CPSO is that its performance also degrades rapidly as the dimensionality increases, and this problem will be magnified when applied to non-separable functions due to parameter interactions. Regardless of different approaches, successful implementation of co-evolution requires the explicit consideration of several design issues such as problem decomposition and parameter interactions.

In the few years, the quantum mechanical computational theory is attracting serious attention since their remarkable superiority was demonstrated by several quantum algorithms [36,37]. Quantum-inspired evolutionary algorithm (QEA), proposed by Han and Kim [38], integrated the quantum computing mechanisms and classical evolutionary algorithms and utilized the concepts of quantum bit (Q-bit), superposition of states and collapse of states. Like other EAs, QEA is also characterized by the presentations of individuals, the evaluation function and the population dynamics. However, instead of binary, numeric or symbolic representation, QEA uses a Q-bit as a probabilistic representation which has a better characteristic of population diversity than any other representation. Thus a Q-bit individual has the advantage that it can represent a linear superposition of states in the search space. Recently, some proposals have combined quantum computation and EAs with great concentrations, as shown in the following:

a. Gu et al. [35] discussed a novel competitive co-evolutionary quantum genetic algorithm for a stochastic job shop scheduling problem.
b. Han and Kim [39] proposed a quantum-inspired evolutionary algorithm with a new termination criterion, gate, and two-phase scheme.
c. Jiao et al. [40] put forward a quantum-inspired immune clone algorithm for global numerical optimization.
d. Mourad [41] proposed a quantum swarm evolutionary algorithm to extract the best rule in reasonable execution time.

Recently, the potentials of quantum computation and mechanics further enlighten researcher to study some efficient quantum-inspired evolutionary algorithms for the solutions of some practical application problems. For example:

a. Lu and Juang [42] presented a region-based quantum evolutionary algorithm (RQEA) for solving numerical optimization problems, and they [43] also proposed another quantum-inspired space search algorithm (QSSA) for global numerical optimization.
b. Neto et al. [44] presented an improved quantum-inspired evolutionary algorithm (IQEA) with diversity information and applied it to economic dispatch problem with prohibited operating zones.
c. Qu et al. [45] proposed a new hybrid quantum clone evolutionary algorithm (HQCEA) in a two-layer networked learning control system architecture.
d. Mariani et al. [46] put forward a chaotic quantum-behaved particle swarm approach and applied it to optimization of heat exchangers.
e. Coelho and Mariani [47] proposed a particle swarm approach based on quantum mechanics and harmonic oscillator potential well for the economic load dispatch with valve-point effects.
f. Wang et al. [48] presented a novel effective differential real-coded quantum-inspired evolutionary algorithm (DRQEA) for solving the short-term hydrothermal generation scheduling.
g. Du et al. [49] proposed a combining quantum-behaved PSO and K2 algorithm for the enhancing gene network construction.

We combine advantages of quantum-inspired evolutionary algorithm and cooperative co-evolution, and propose a novel and efficient minimum attribute reduction algorithm (QSCCAR) based on quantum-inspired self-adaptive cooperative co-evolution incorporated into shuffled frog leaping algorithm. The successful integration of the quantum evolutionary algorithm and cooperative co-evolution expands their respective research fields and indicates a new way for the attribute reduction research. This paper is meaningful for this NP-hard problem of minimum attribute reduction.

The contributions of this paper cover the following:

(1) Self-adaptive cooperative co-evolutionary model (SCCM) for minimum attribute reduction. It is adopted to group the interacting attribute decision variables into one subpopulation with the self-adaptive mechanism according to their historical performance. Since different group sizes capture different interacting levels between original attribute sets, SCCM can self-adapt attribute subsets' sizes among different levels.
(2) Quantum-inspired shuffled frog leaping algorithm (QSFLA). It is chosen as the subpopulation optimizer of the decomposed subsets. Each evolutionary frog individual is represented by