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Modified cultural-based genetic algorithm for process optimization

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Abstract The main weak points in using AI optimization technique are the possibility of being trapped at local minima, being confined to the population space, difficulty to solve heavily nonlinear problems and to make full use of the historical information beside the lack of prediction about the search space. In this paper, a hybrid optimization technique; namely culture-based genetic algorithm is proposed and tested against three multidimensional and highly nonlinear real world applications. This method proved to overcome most of these problems and the results showed that the proposed algorithm gives excellent performance for pressure vessel design and fed-batch fermentor problems.

1. Introduction

Hybrid intelligent algorithms have been focused on by many researches due to its ability to obtain better results according to the combination of those intelligent algorithms with mutual complementary [1–4]. No Free Lunch theorem indicates that there is no single method could solve all optimal problems. However, it is possible to develop a hybrid or integrated algorithm so as to improve the performance of whole algorithm.

Metaheuristics algorithms such as genetic algorithms GA make up another class of search methods that has been adopted to efficiently solve dynamic optimization problem due to their excellent performance in solving combinatorial optimization problems [5–10]. However, most of these methods are confined to the population space and in addition the solutions of nonlinear problems become quite difficult especially when they are heavily constrained. They do not make full use of the historical information and lack prediction about the search space.

Aiming at these problems, researchers have put forward various methods. Since in heavily constrained model, generating solutions in the unfeasible region is time consuming. Culture algorithm (CA) [11–16], can benefit from the history of violation and satisfaction of these constraints and force the algorithm to move faster and converge better. This history is used to force the evolution process away from the region that

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violates the constraints at each generation. This kind of information is updated to reduce the need for immature individual which wastes energy by bypassing trial and error iterations which usually requires to acquire information about the environment, and also enables the transmission of more information than any individual genome may feasibly contain. Culture affords populations with flexibility where cultural information can be transmitted faster than genetic material and stability where culture is capable of persisting beyond the lifetime of a single individual.

In human societies, culture can be viewed as a vehicle for the storage of information that is potentially accessible to all members of the society, and that can be useful in guiding their problem solving directions [11].

Cultural Algorithms consist of a social population and a belief space [14–17] as shown in Fig. 1. Selected individuals from the population space contribute to cultural knowledge by means of the acceptance function. The cultural knowledge resides in the belief space where it is stored and updated based on individual experiences and their successes or failures. In turn, the cultural knowledge controls the evolution of the population by means of an influence function [18]. There are at least five basic categories of cultural knowledge that are important in the belief space of any cultural evolution model: situational, normative, topographic, historical or temporal, and domain knowledge [19].

Reynolds et al. [20] and Chung and Reynolds [18] investigated the use of cultural algorithms for global optimization with very encouraging results. Their work did not totally use all different sources of information in the belief space. Kobti et al. [19] used only the topographic, domain knowledge and historical knowledge. Xue and Guo [11] abstracted four different kinds of knowledge and succeeded in using the range of the best parameters to be one source of belief information, and then this was followed by accepting the point or modifying it to be in the proper region. To solve the earliness/tardiness flow shop with uncertain processing time only the situational knowledge and information relating to the best point are implemented by Yu and Gu [12].

The pseudo code of the general CA is as follows:

- Begin
- t = 0;
- Initialize Belief Space *BLF(t)*;
- Initialize Population Space *POP(t)*;(in the *BESTRANGE*)

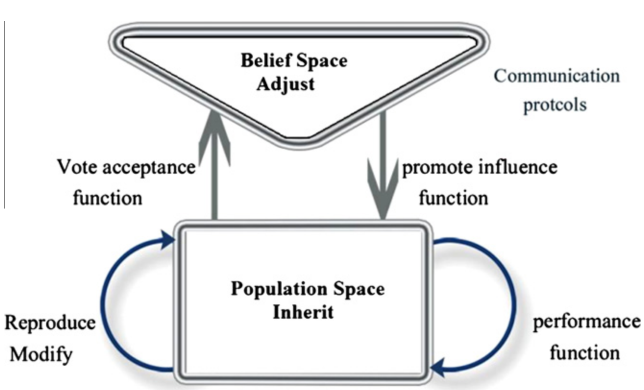

Figure 1 Culture algorithm CA components.

- Repeat until termination condition achieved;
  - Perform actions of the individuals in *POP(t)*;
  - Evaluate each individual by using the fitness function;
  - Select the best individuals to become parents;
  - Create new generation of offspring by mutation & crossover;
  - Delete not so fit members to make room for the new ones;
  - *bLF(t)* alters the genome of the offspring - influence function;
  - Best individuals can update the *BLF(t)* – acceptance function;
- End.

The following sections of this paper are organized as follows. Section 2 introduces a more general investigation into the potential strength of the modified cultural based real coded genetic algorithm MCBGA. Section 3 covers results and computer simulations after applying the proposed MCBGA on different common applications.

2. Culture genetic algorithm

The proposed research has employed real-coded GA integrated with culture algorithm. Real coded GA requires low memory to run, has high precision, and easy to search in large space, meanwhile it avoids the troublesome encoding and decoding process of computing the objective function. It has been reported that real coded GA outperforms binary-coded GA in many design problems [21,22]. In the belief space there are multi sources of information that the best individuals along their evolution are stored. The main source of information implemented in the belief space are: The list of best points along all generations (*LISTBEST*), the ranges of the best performers' candidates (best range for the 20% best chromosomes in POP) (*BESTRANGE*) to create some chromosomes "solution" in this range, and the ranges of feasible regions (*FRANGE*) in which random individuals are generated in that satisfy the constraint and lead the search away from candidates that violate the constraints. The algorithm is detailed below.

- Begin
- *t* = 0;
- Initialize Population Space *POP(t)*;
- Initialize Belief Space *BLF(t)*;(*LISTBEST, BESTRANGE, FRANGE*)
- Repeat until termination condition achieved;
  - Perform actions of the individuals in *POP(t)*;
  - Evaluate each individual by using the fitness function;
  - Penalize fitness if violation happened
  - Select the best individuals to become parents;
  - Create new generation of offspring by crossover;
  - Influence function: move all individuals toward the best candidate, choose the best percent of them