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Towards Optimizing the Cultural Algorithms Performance

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ABSTRACT

As long as humankind exists, he tries to excel in all areas and will to the greatest degree of happiness with the least attempt. Evolution in human societies is not only based on personal experiences, but the condition of progress of any human society is based on preserving and applying the experiences and knowledge acquired from individuals in during different generations. These experiences would form culture of a population. The evolutionary algorithm, which uses the culture, would be known as cultural algorithm. One of the shortcomings of these algorithms is formation of a culture, and following of all people of the same culture that is trapping into involving in local optimums during evolution. To overcome this defect, many various algorithms have been applied. In this paper coincides with pareto ranking, a new method is introduced with the changes in functions and spaces of cultural algorithms such as production of some norm knowledge instead of knowledge, pay attention to not strong people with more improvement and multi-step promoting in ranking to other people, use some leaders to update the belief space and creating some modifications in influence function as any person in the population is influence under the nearest beliefs and culture. The results referred to the increase of convergence speed of new proposed method to its standard type.

KEYWORDS: Optimization, Cultural algorithms, Evolutionary algorithms, Genetic algorithms, Pareto ranking.

1. INTRODUCTION

One of the most fundamental principles in the world is optimal condition being started of a small world as microscopic world in which the atoms in physics attempt to form limitations for energy minimization of the electrons, and continues to biological principles of Principle of survival of the fittest. This trend at the same time with biological evolution led into the better adjustment of the species with the environment. Here a local optimum is a well-adjusted species overcoming all the surrounding agents.

Thus, optimization is one of the oldest sciences that are developed even in routine life. Many various algorithms are applied for optimization of the functions and mostly for the start, produced random values and then they were corrected repeatedly. In these repetitions, it is possible to lose the good solution again. Thus, these algorithms hold the solutions in a set called optimum set.

The first generation of the algorithms is genetic algorithms attempting to get model of human being genetic structure and transferring the genetic attributes from the parents to the children. The point that is ignored in all the algorithms is the role of achieved experiences and knowledge during consecutive generations in the evolution of societies namely human being communities.

Cultural algorithms are based on the theory that in advanced communities, besides the knowledge a person has in genetic secrete, inherited his ancestors and there is another element for evolution. The culture can be like a set of resources and people put their achieving knowledge after some years. When a new person have access to this knowledge library, can learn the things not experienced directly. Thus, new people have a library of knowledge not experiencing it directly. The progresses that the human being achieved as complete set owe to this culture. Culture is the set of accepted beliefs of the best people of the society.

One of the most important shortcomings of these algorithms is formation of a culture and following of all people of the same culture that is leading into involving in local optimums during evolution. Here, pareto ranking method is introduced and its applications are applied in solving the problems with limitation, some attributes of the word overcoming this method and ranking stages are investigated. Finally, the modifications in the existing functions and structures in cultural algorithms are used to adjust with ranking method including the production of some norm knowledge instead of knowledge, pay attention to not strong people with more improvement and multi-step promoting in ranking to other people, creating some modifications in acceptance function as some leaders are used to update the belief space and creating some modifications in influence function as any person in the population is under the nearest influence of beliefs and culture. The proposed algorithm was evaluated by solving a benchmark problem and its results are compared with the results of solving the problems by standard cultural algorithm in the form of diagram and tables.

This paper is organized as the following. Section 2, provides review of related works. In section 3 cultural algorithms are introduced briefly. Section 4, focuses on pareto optimization method. Then, in section 5, the proposed

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methods are presented. In section 6, the results of the experiments are analyzed and compared. Finally, section 7, draws conclusion.

1. Related work

Normally, optimization algorithms can be divided into two basic classes: Deterministic and probabilistic algorithms [17]. Deterministic algorithms are used when there is an evident relation between the attributes of possible solutions and their applications for a deterministic problem. Thus, search space can be searched effectively by division and overcome techniques. If the relation between a candid solution and its fitness is not observed, candid solutions can be considerably different in terms of their application [7]. If the dimensions of search space are big, the solution of the problem is more difficult deterministically. Thus, Monte Carlo Simulations (MCS) as a probabilistic algorithms are defined [6,15,18]. [14] used neural networks and MCS to deal with reliability-based optimization. [10] used Monte Carlo Simulations coupled with Genetic Algorithms to optimize the off-target frequency caused by uncertainty as one of the objectives. In [15], MCS was used to reduce the number of finite element simulation evaluations, as well as different response surface methods. The Classification of optimization algorithms is shown in figure 1.

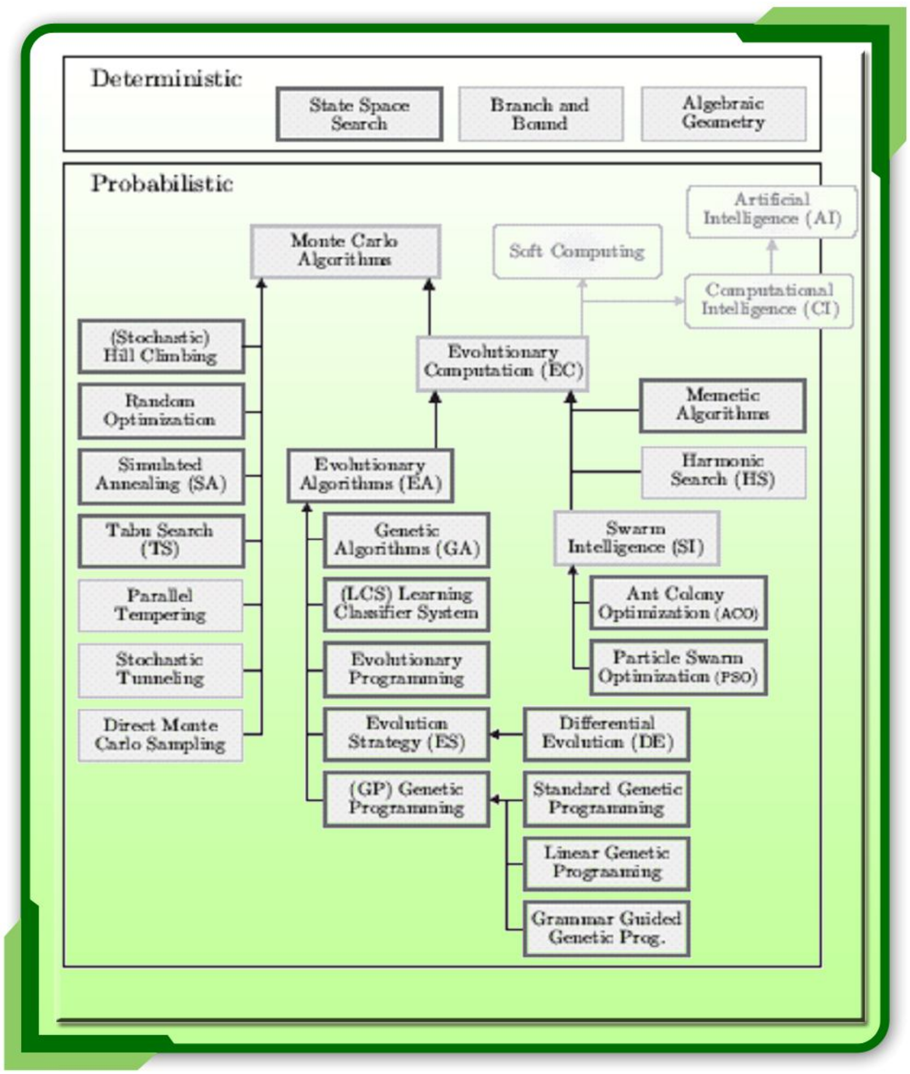

Fig. 1. Classification of optimization algorithms [16]

Heuristics used for global optimization. They are functions that make decisions about which of candidate solutions is may be examined next test, or how the next individual can be produced. Heuristics could well be used in both deterministic and probabilistic algorithms. In addition, deterministic algorithms usually employ heuristics to determine processing order of the solution candidates. Probabilistic methods, may only consider those elements of the search space in further computations that have been selected by the heuristic [12]. Heuristics are usually problem class dependent [16].

A Meta heuristic is a method for solving very general classes of problems that combines objective functions or heuristics in an abstract for greater efficiency [8]. They are often performing based on natural phenomenon or physical process [16]. Simulated annealing, for example, decides which solution candidate to be evaluated next according to the Boltzmann probability factor of atom configurations of solidifying metal melts. Evolutionary algorithms copy natural evolution behavior. They consider solution candidates as individuals that compete in a virtual environment [5].

An important class of probabilistic Monte Carlo Meta heuristics is Evolutionary Computation that includes all algorithms based on a set of multiple solution candidates (called population) that are frequently being refined. This field of optimization is also a class of Soft Computing as well as a part of the artificial intelligence area [16]. Cultural algorithm defined the evolution of culture element from an evolutionary computation system over the time. This culture element is an explicit mechanism for achieving, storing and integration of behavior and experiences of problem solving of the group and person [9]. In addition, traditional techniques of evolutionary calculations only apply implicit mechanisms to display and store the achieved knowledge of the people transferring from one generation to another [4]. [1] after introduction of cultural algorithm components and using cultural algorithms technique achieved an optimized design of pressure vessel.

2. Cultural Algorithms

As mentioned, the first generation of the algorithms is genetic algorithms attempting to get model of human being genetic structure and transferring the genetic attributes from the parents to the children. If there are some people with more output in the society (better answer for the problem) and can be applied to produce new children, by mutation of two parents or creating random changes in parent genes. Later, by making the model of animal and human populations as birds, fishes and termites, other algorithms were created achieving better answers and based on more intelligence to genetic algorithms. The point that is ignored in all the algorithms is the role of achieved experiences and knowledge during consecutive generations in the evolution of societies namely human being communities.

Cultural algorithm can be considered as two-inheritance system and the evolution in it is occurred in population and belief. Two parts interact via protocol. The protocol determines the acceptable people with the ability of updating the belief space. In addition, the protocol determines how the update beliefs can influence the adjusting of population. The basic framework that is applied to support the definition of cultural algorithm was shown in Figure 2 [3]. This paper supports the population models applied real-valued for function optimization. The existing knowledge is in corresponding belief with the required information to understand the constraints of the problem.

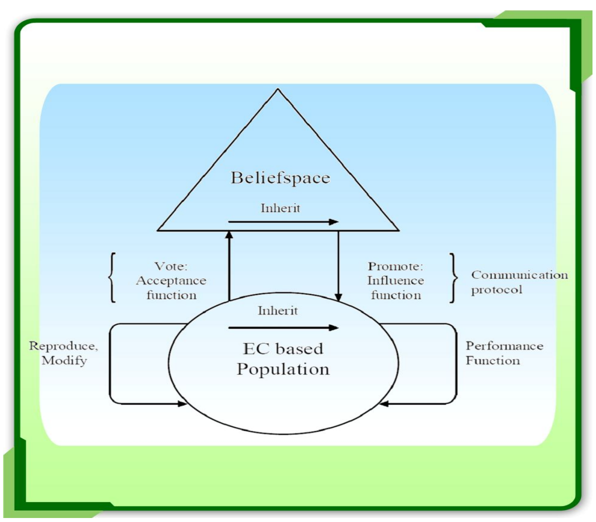

Fig. 2. Cultural algorithm framework [3]

3. Pareto optimization

Pareto ranking method has been used to solve constrained optimization. The first step in this method is to rank the population. The formal definition of ranking in the evolutionary algorithms is that, the population individuals have to be sorted by dominance. When two individuals are compared, the dominance is expressed as follow[2]:

- If both individuals are feasible, the one with better fitness is the non-dominated individual.
- If one of the individuals is feasible, that is selected.
- If both individuals are infeasible, the one with the least constraints violated is selected.

[13] used a swarm-based Pareto ranking strategy for solving constrained optimization problems. The strategy has not been developed for cultural algorithm, but since it is swarm-based, this paper has adapted it for cultural algorithm.

Assuming a minimization problem, the general constrained problem is defined as:

$$\begin{array}{lll} \text{minimize} & f(x), & x=(x_1,x_2,\ldots,x_{nx}) \\ \text{Subject to} & g_m(x) \le 0, & m=1,\ldots,n_g \\ & h_m(x) = 0, & m=n_g+1,\ldots,n_g+n_h \end{array}$$

For each individual, a constraint satisfaction vector, $u_i(t)=(u_{i1}(t) , u_{i2}(t) ,\ldots, u_{inu}(t))$, is calculated as following equation.

$$u_{im}(t) = \begin{cases} 0 & \text{if constraint } m \text{ is satisfied} \quad 1 \le m \le n_u \\ -g_m(X(t)) & \text{if constraint } m \text{ is violated} \quad 1 \le m \le n_g \\ -\delta \pm h_m(X(t)) & \text{if constraint } m \text{ is violated} \quad n_g+1 \le m \le n_g+n_h \\ & \text{, if } h_m > 0 \text{ '+' else '-' is selected} \end{cases}$$

Where n_g and n_h are the number of inequality and equality constraints respectively. Using these constraint vectors, a constraint matrix as shown in Figure 3 is defined for an individual in t^{th} generation.

$$\mathrm{U}(t) = \begin{bmatrix} u_{11}(t) & u_{12}(t) & \ldots & u_{1n_u}(t) \\ u_{21}(t) & u_{22}(t) & \ldots & u_{2n_u}(t) \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ u_{n_s 1}(t) & u_{n_s 2}(t) & \ldots & u_{n_s n_u}(t) \end{bmatrix}$$

Fig. 3. The constraint matrix

The constraint matrix $U(t)$ is used to rank individuals based on dominance. The process starts by assuming all non-dominated individuals a rank of 1. All the rank 1 individuals are then removed from the population. The process continues until all individuals are ranked. Adjustment of individuals is based on information exchange between leaders and individuals. Leaders are selected as follows: if the number of rank 1 individual is between 10 and 50 (%) of population size, then all rank 1 individuals are selected as leaders. And if the number is less than 10%, some individuals with next rank(s) are selected, to reach 10% of the population, as leaders. This process is used for all current population people until all people have rank. All justified people as non-dominant get rank 1 and the people are adjusted based on information exchange between the leaders and people.

4. Proposed method

As already mentioned, the belief space determines the direction and step size of evolution, but it may represent a local optimum, instead of the global optimum. Therefore, the diversity with respect to entire search space will be decreased and the algorithm will likely be trapped into local optima. This limitation can be overcome by creating and maintaining several normative knowledge sources, the number of which is the percentage of the total population size which given by user, within belief space. Therefore, each subpopulation will be guided by the corresponding culture. This approach can be implemented by applying the Pareto ranking method into the cultural algorithm. But this work requires some change in the components and functions of the cultural algorithm.

4.1 The acceptance function

Improving the belief space knowledge resources, to make the stored knowledge real during optimization process, some modifications are done in acceptance function as only positive changes were not made in the best people to make the belief space update. On the contrary, it depends upon the improving amount of not strong people with more improvement and multi-step promoting in ranking to other people are used in acceptance function. In new acceptance function the obtained leaders by Pareto ranking method will be selected as influence individuals in belief space. The remaining steps of the function are the same used in standard cultural algorithm.

4.2 Updating belief space

In this method for updating the belief space, each normative knowledge source is updated under the influence of closest leaders, selected by the new acceptance function; the closest leaders are ones that have the lowest Euclidean distance to the normative knowledge center. The other steps of updating belief space are the same used in standard cultural Algorithm. Figure 4 gives a pseudo code of the new updating function.

```
update beliefspace()
begin
  For each normative knowledge source in the belief
  space
      Select %p of the nearest leaders to the normative
      center
      Update   the normative using selected leaders
  End for
end
```

Fig. 4. The new updating function.

4.3 Customizing influence function

In the standard influence function, all of the population's individuals were mutated under the influencing one normative knowledge source but in the new approach, each normative source will affect the closest individuals to itself with the minimum Euclidian distance, and other stages of this phase are done standard. Figure 5 shows this influence function.

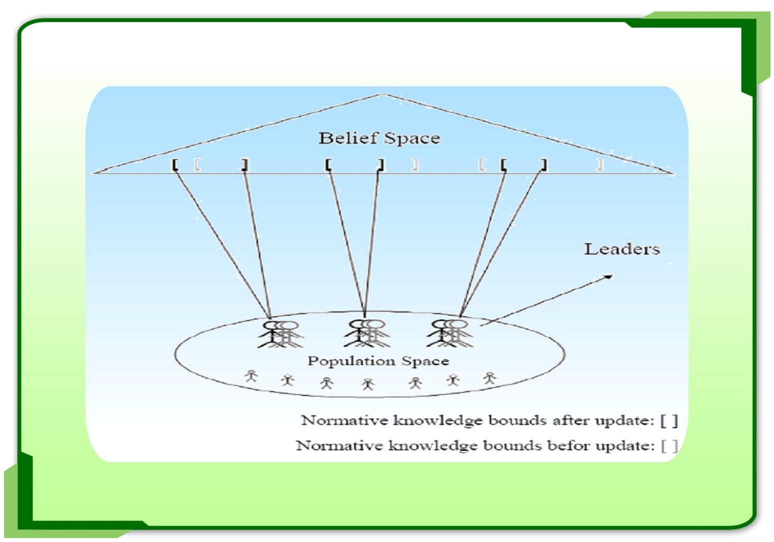

Fig. 5. Updating normative knowledge's bounds by the closest leaders

Figure 6 shows the influence of belief space of the proposed method in the population.

$$x_{n+i,j} = \begin{cases} x_{i,j} + \left|\text{distance}_{near\_nor_j,i} \times N_{i,j}(0,1)\right| & \text{if } x_{i,j} < sit_j \\ x_{i,j} - \left|\text{distance}_{near\_nor_j,i} \times N_{i,j}(0,1)\right| & \text{if } x_{i,j} > sit_j \\ x_{i,j} + \text{distance}_{near\_nor_j,i} \times N_{i,j}(0,1) & \text{otherwise} \end{cases}$$

$$\text{distance}_{near\_nor_j,i} = nearest\_norm_i(j,1) - nearest\_norm_i(j,2)$$

$$nearest\_norm_i = \text{closest } central\_norm_k \text{ To } i^{th} \text{ individual} \quad k = 1,\dots,m$$

$$central\_norm_k = \left\{(central\_norm_k(j,1) + central\_norm_k(j,1))/2 \mid j = 1,\dots,n\right\}$$

$$N_{i,j}(\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{x_{i,j}-\mu}{\sigma}\right)^2}$$

Fig. 6. The influence of belief space of the proposed method in the population

Where i is the number of person, j the number of gene, $N_{i,j}(0,1)$ Guassian random value for j^{th} gene from person i^{th} with the average μ =0 and variance σ^2=1, n is the number of genes of each person, m is the number of normative knowledge of the knowledge space, $nearest\_norm_i$ is the nearest normative knowledge to person i^{th}, $central\_norm_k$ is the center of upper and lower boundary center of normative knowledge k^{th}.

5. The evaluation and comparison of the experimental results

The following benchmark function is used for testing and evaluating the proposed method [11].

$$\max \quad f(X) = x_1(70 - 4x_1) + x_2(150 - 15x_2) - 100 - 15x_1 - 15x_2$$

where

$$0 \le x_1 \le 10$$
$$0 \le x2 \le 10$$

The results of optimization of function with the proposed method and standard algorithm are shown in Table 1. As is shown in the following table, using Pareto ranking method in cultural algorithm increased the convergence velocity. The important point here is such that the algorithms on a one processor, with similar population (200) and similar generations' number (20) were performed.

Table 1: The comparison of the results of proposed algorithm with standard cultural algorithm

Description	Cultural algorithm	Proposed method
Generation of the best result	15	4
Generation average of the best results*	17	9
x1	6.8761	6.8761
x2	4.4993	4.4993
The best result	392.8125	392.8125

*Averages are calculated for 20 times performance

Figures 4 and 6 show the convergence diagram of two above algorithms.

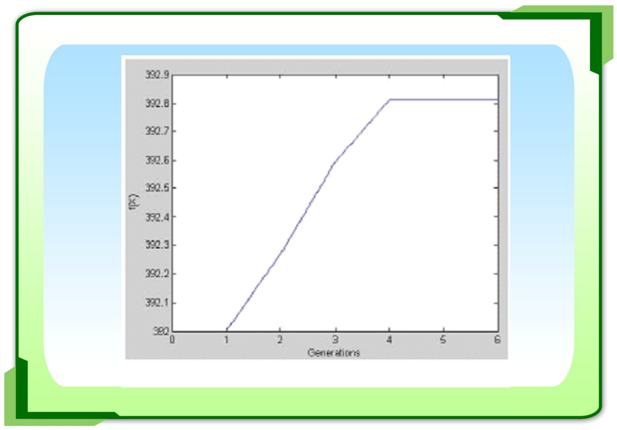

Fig. 4. Optimization convergence diagram of benchmark function in the proposed method

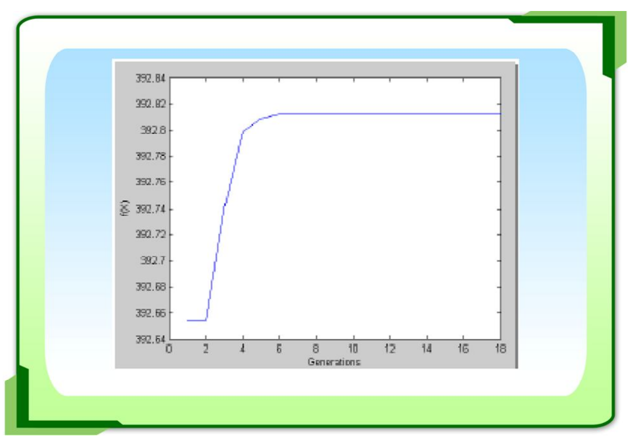

Fig. 5. Optimization convergence diagram of benchmark function in standard cultural algorithm

6. Conclusion

In this paper, at first, the classification of optimization algorithms based on Deterministic and probabilistic algorithms were introduced. The kind of the evolutionary algorithms has been defined which based on the culture and the beliefs would be created in during of evolutionary process. Then a dominance-based method known as pareto ranking method, was described which the basis of the work was in the first priority on the lack of disobey of limitations, and in the second priority on fitness function. Due to the selection of leaders and producing various sub-populations, increased the variety among the existing people in the population and searching distribution in all justified space. By applying the mentioned method in cultural algorithm and some modifications in belief space, acceptance function and influence function, a new algorithm was presented depending upon the leaders determined in new acceptance function. In the proposed method, population space was separated to some sub-population and for each sub-population, good belief space was produced. The normative knowledge formed for each sub-population was updated being affected by corresponding leaders and the same path was repeated of belief space to population space. In other words, sub-population is completed affected by the nearest normative knowledge and the population of children was the result of this influence. Indicated the new algorithm causes increasing convergence rate in the cultural algorithm.

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