Indian J.Sci.Res.3(2) : 33-39, 2012

OPTIMIZATION OF CULTURAL ALGORITHMS STRUCTURE BASED ON PARETO RANKING

SAYED OMID AZARKASB[1]

Artificial Intelligence MSc, Faculty of Computer Engineering, Qazvin Branch Islamic Azad University, Tehran, Iran
E-mail : azarkasb@ymail.com

ABSTRACT

The progress of generation of human being cannot be completely dependent upon genetics changes. Human interactions, social behavior and other factors have important role in optimization process. As social interactions allow rapid adjustment and progress compared to genetics, an optimization algorithm can be including social factors in convergence speed. These attributes can be transferred from one generation to another as genetic code later. Such attributes by the culture and algorithms being used are called cultural algorithms. One of the shortcomings of the algorithms is forming a culture and following all the people of the culture involving the local optimum during the evolution period. To remove this problem in this paper, a method called Pareto ranking was used to select the leaders and increasing the variety in the generations of this algorithm. The results referred to the increase of convergence speed of new combination method to its standard type.

KEYWORDS: Cultural algorithms, evolutionary algorithms, genetic algorithms, optimization

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 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. In this paper, a method called Pareto ranking was used to improve this problem. Based on the main focus of pareto method on the lack of disobey of people of the limitations applied by the problem and also using some leaders. Some changes in the existing structures and functions were created in cultural algorithms that priority to the lack of display of the limitations, besides creating some cultures, a population is divided into some sub-populations (each sub-population close to a one culture) and all space is searched.

This paper is organized as the following. Section 2, provides review of related works. In section 3 multi-objective optimization, pareto optimization method and its use in cultural algorithms were introduced. Section 4, focuses on Ackley function was used as standard criterion to compare the efficiency of evolutionary algorithms. Then, in section 5, the proposed method is introduced. In section 6, the results of the proposed method are analyzed and are compared by other algorithms. Finally, section 7, draws conclusion.

RELATED WORK

From the view of artificial intelligence, cultural algorithms can be observed as heuristic (evolutionary algorithm) with the knowledge range of searching process before being provided as default. Some of the social researchers referred to the point that culture can be coded as symbolical and being transferred between the populations (Chung and Reynolds, 1998). As other mechanism of inheritance, by this idea (Reynolds,1994) a computation model in which cultural evolution was raised as evolutionary process acting as inheritance process in two levels: Micro evolutionary level and Macro evolutionary level.

In micro evolutionary level, the people are described based on their behavioral characteristics (that can be acceptable in terms of social aspects or unacceptable). These behavior characteristics are transferred from one generation to another by some social dynamics operator. In macro evolutionary level, people can produce omappa

[1]Corresponding author

(Renfrew, 1994) or general description of their experiences. Mappa person by forming a group of mappa by a set of public operators and problem specific issues can be combined or modified. Both levels share a communication line.

Reynolds, 1994 by genetic algorithms for micro evolutionary modeling and (Mitchell, 1978) version space are proposed for modeling macro evolutionary process of an evolutionary algorithm. If we use a cultural algorithm for overall optimization, the acceptable beliefs can be seen as constraints guiding the population in micro evolutionary level (Michalewicz, 1995). 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 (Jin and Reynolds, 1999). 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 (Coello Coello and Becerra, 2002).

On the other hand, Cultural algorithms allow people to interact in various methods by various forms including reflecting symbolic information of complex cultural systems. Basic cultural algorithm allows the people to communicate via common belief space. Belief space that can be stored as cognitively or symbolic that can be shared.

It is well clear that evaluation of the interaction inside the complex systems is affected by structure nature revealed of the interaction between the people of the system (Reynolds et al., 2005). In cultural evolution process, it is used as a tool to improve the behavior of a person or group or commonplace. The people at first by performance function are evaluated. Performance data show the skill of problem solving by a person. Acceptance function shows which people in the current population can influence the current beliefs. The skills of these people and other people is adjusted and combined for the group of beliefs. The beliefs group is used to guide the population changes in the next step. (Azarkasb and Naderi A., 2012) after introduction of cultural algorithm components and using cultural algorithms technique achieved an optimized design of pressure vessel.

OPTIMIZATION

Multi-Objective Optimization

Global optimization techniques are not used only for finding the minimum and maximum of single objective functions *f*. In most of real world designs or decision making problems, to define f_i of n functions was used showing some criteria (Mitchell, 1978).

$$F \quad f_i : X \quad Y_i : 0 \quad i \quad n, Y_i \quad R$$

The designed algorithms for optimization of some sets of *F* of objective functions are called multi-objective prefix. Multi-objective optimization is mostly including involving objectives, for example, when it is attempted that a machine is built rapid and environment friendly. In such conditions, there is more than one optimized solution. Thus, overall optimization is finding the solutions that are good and are different in most cases.

Pareto Optimization

Some words as Pareto Optimality and dominance are more used in multi-objective optimization. Pareto ranking and dominance are used to solve the problems with limitations. In the following we explain about the initial concepts and working with them and using them in cultural algorithms.

Dominance

Dominance in multi-objective issues is defined as the following during the comparison of two particles (Becerra and Coello Coello, 2006).

If two particles are justified, the best fitting particle is non-dominance particle or the particle dominating the other particle.

If one of the particles is justified, the particle is non-dominant.

If two particles are not justified, the particle is non-dominance with less disobey of the limitation.

Ranking

The definition that can be presented of ranking as general in population evolution field is such that, at first the people are valued based on some variables as fitting, disobey of the limitations and etc. Then, based on the priorities (e.g. the first priority is the minimum amount of disobey of limitations and the second priority is the maximization of fitting amount) is ordered and according to the position of each person, a rank is given to it to take good decisions in next stages based on the ranks.

Initial Actions

Nanvala and Awari, 2011 used the strategy of pareto ranking based on population to solve optimization problems with limitation. As this view is based on population, easily it can be used in cultural algorithms. For each person, a limitation fulfilling vector $u_i(t)=(u_{i1}(t), u_{i2}(t), \ldots, u_{inu}(t))$ is calculated as Equation 1.

$$u_{im}(t)= \begin{cases} 0 & \text{if constraint m is satisfied,} \quad 1 \le m \le Nu \\ gm(X(t)) & \text{if constraint m is violated ,} \quad 1 \le m \le Nu \end{cases}$$

Eq. 1: The calculation of limitation fulfillment vector

Where i is the number of person (chromosome), m the number of applied limitation and n_u the sum of existing limitations in the problem. By the limitation vectors, a limitation matrix is defined for the population in each generation (Fig.1).

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

Fig. 1: Limitation fulfillment matrix

Limitation matrix U(t) is used for ranking the people based on their disobey of each person to the limitations. The process by considering rank 1 is started for the person or people with least disobey (based on priority of this paper that the fitting of each person is in the second priority) and maximum fitting is started. Then, this person is eliminated of the population and is stored in another place. 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.

Ackley Function

Due to considerable local minimums in state space of Ackley function, it is caused that this function is used as standard criterion to compare the efficiency of various evolutionary algorithms. Equation 2 shows Ackley function in two-dimensional space (Grosan et al., 2011).

$$\min f(x_1,x_2) = -c_1.\exp\left(-c_2\sqrt{\frac{1}{2}\sum_{j=1}^{2} x_j^2}\right) - \exp\left(\frac{1}{2}\sum_{j=1}^{2}\cos(c_3.x_j)\right) + c_1 + e$$

$$5 \le x_j \le 5$$

$$c_1 \quad 20 \quad c_2 \quad 0.2 \quad c_3 \quad 2\pi \quad e \quad 2.71282$$

Eq. 2: Ackley function

Proposed Method

To use Pareto ranking method in our proposed method, we need some changes in cultural algorithms structure are mentioned flowing.

Acceptance Function Change

The change in this method to the cultural algorithm standard is such that is extracted of the leaders by Pareto ranking method, to select effective people in updating the belief space, and other stages of this phase are done according to standard trend. If the variable is a non-justified cell, it is attempted that it is moved to the closest semi-justified cell, it is attempted that it is moved to the closest justified cell. If none of the methods is possible, we try to move it to a random location inside the distance difference in norm section. The leaders are selected as following method: If the number of people with the rank more than 1 are not more than 50% and less than 10% of the number of existing people in the population, all people with rank 1 are selected as leader. If they are less than 10% of the existing people in the population, the people with higher ranks can be selected as leader. The facts that finally what percent of the population are selected as leader are dependent upon the applied solutions by the algorithm. The justified people are the ones affecting the other people. In this case, instead of one population, we can have some different sub-populations with leaders and the variety of people is increased in search space. Each person for information exchange selects the closest leader and is inclined to him. These sub-populations are related for the best existing person in whole population space.

distance($norm_i$,$leadre_j$) is the Euclidian distance between normative knowledge ith and leader jth, is the central point of knowledge i for variable k, Ui,k , Li,k were upper and lower boundaries of normative knowledge ith for variable k. i is normative knowledge number, j the number of gene, n the number of genes of each person, Li,j lower

```
Update beliefspace()
    begin
     for i=1 to n_normative
         for j=1 to n_leaders
                 Calc_distance(i,j )
          end
         Near_leaders(i) =Select (%p* n_leaders) from the nearest leaders to i th
              Update _normative(i , Near_leaders(i))
     end
end
```

```
Calc_distance(i,j)
  begin
     distance(norm_i,leadre_j) = sqrt( sum_{k=1}^{n} (leader_{j,k} - central_norm_{i,k})^2 )
    // norm_central_{i,k} =(U_{i,k}+L_{i,k})/2
  end
Update _normative(i , Near_leaders)
begin
  for j=1 to n
    If min(near_leaders (j)) < L_{i,j} or fitness (individual_{minnear_leaders (j)}) < fitness(L_{i,j} )
        L_{i,j} = min(near_leaders (j))
        fitness(L_{i,j} )=fitness (individual_{minnear_leaders (j)})
    end if
    If max(near_leaders (j)) > U_{i,j} or fitness (individual_{maxnear_leaders (j)}) < fitness(U_{i,j} )
        U_{i,j} = max(near_leaders (j))
        fitness(U_{i,j})=fitness (individual_{maxnear_leaders (j)})
     end if
end
```

$$distance(norm_i,leadre_j) = \sqrt{\sum_{k=1}^{n} (leader_{j,k} - central\_norm_{i,k})^2}$$

Figure 2 shows pseudo code of updating belief space

bound of normative knowledge with gene jth of knowledge ith, Ui,j upper bound of normative knowledge corresponding with gene jth of knowledge ith, min(near_leaders (j)) is the smallest gene of jth among leaders in the proximity of normative knowledge and max(near_leaders (j)) is the greatest gene jth among leaders of normative knowledge. Figure 3 shows the update of normative knowledge.

The Change in Updating Belief Space

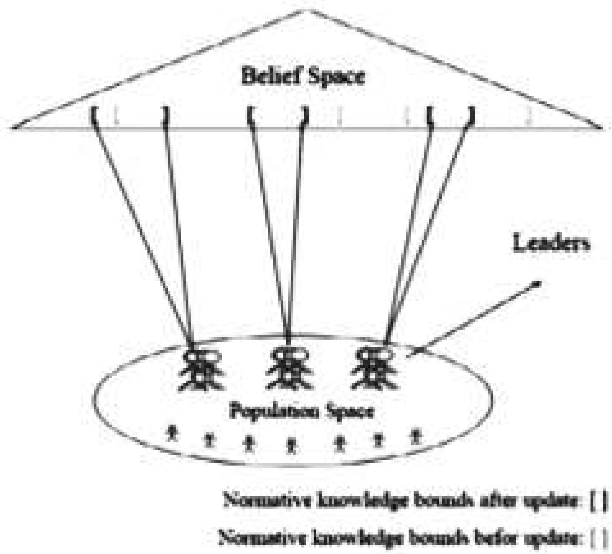

Fig. 3. Updating normative knowledge

The change that is created to the standard cultural algorithms is such that instead of having a normative knowledge, some normative knowledge (a percent of total population that is determined by the user is 30% in this paper) is considered in belief space. Updating the norm is such that each norm is affected by the closest leaders selected in updating accepting stage. To find the closest leaders, the Euclidean distance between them and norm is calculated and the people with least distance of a norm are used to update the norm.

The Change of Influence Function in the Population

The change that is done to the standard cultural algorithms is such that all the existing people in the population are not affected by a norm. In addition, each person is influenced by the closest norm with the minimum Euclidian distance is mutated, and other stages of this phase are done standard. Equation 3 shows the influence of belief space of the proposed method in the population.

Where i is the number of person, j the number of gene, Guassian random value for jth gene from person ith with the average =0 and variance =1, n is the number of genes of each person, m is the number of normative knowledge of the knowledge space, is the nearest normative knowledge to person ith, is the center of upper

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

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

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

$$central\_norm_k \quad (central\_norm_k(j,1) \quad central\_norm_k(j,1))/2 \,|\, j \quad 1,\ldots,n$$

$$N_{i,j}(\ , \ ^2) \quad \frac{1}{\sqrt{2 \quad ^2}} e^{\frac{1}{2}\left(\frac{x_{i,j}}{\quad}\right)^2}$$

Eq. 3: The influence of belief space of the proposed method in the population and lower boundary center of normative knowledge *k*th.

The Evaluation and Comparison of the Experimental Results

In this section, to evaluate the propose method, the results of optimization of Ackley function with the proposed method and the results of optimizations of this function by other algorithms are shown in Table 1.

The results showed the increase of convergence velocity in the method to other algorithms namely standard cultural algorithm. The important point is that the determined parameters in three algorithms (standard cultural algorithm, cultural algorithm by Pareto ranking and PSO algorithm) are similar.

Figures 4, 5 and 6 show the convergence chart of three above algorithms.

CONCLUSION

In this paper, another type of evolutionary algorithms are explained as the basis of the movement of formed beliefs and cultures during evolutionary process, not transferring the properties of the parents to the children via random operators as mutation and crossover that are used in genetic algorithms and not following a person namely global best (PSO). Then, one of the dominance-based methods called pareto ranking method was explained 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

Table 1: The comparison of the results of proposed algorithm with other algorithms

Description	Publication Size	Generation number of the best result	*Average of the best result Generation	x1	x2	The best result
Particle Swarm Algorithm	63	58	60	-4.597×10^{-6}	6.349×10^{-6}	2.2172×10^{-5}
Cultural Algorithm Standard	54	52	60	2.300×10^{-16}	-2.916×10^{-16}	8.8818×10^{-16}
Cultural Algorithm With Pareto Ranking Method	36	34	60	-1.350×10^{-16}	9.8000×10^{-18}	8.8818×10^{-16}

* The averages are calculated for 20 times performance

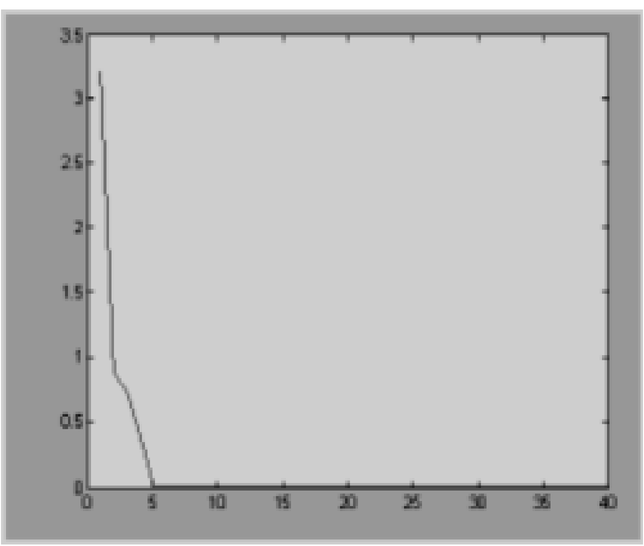

Fig. 4. Optimization convergence chart of Ackley function in the proposed method

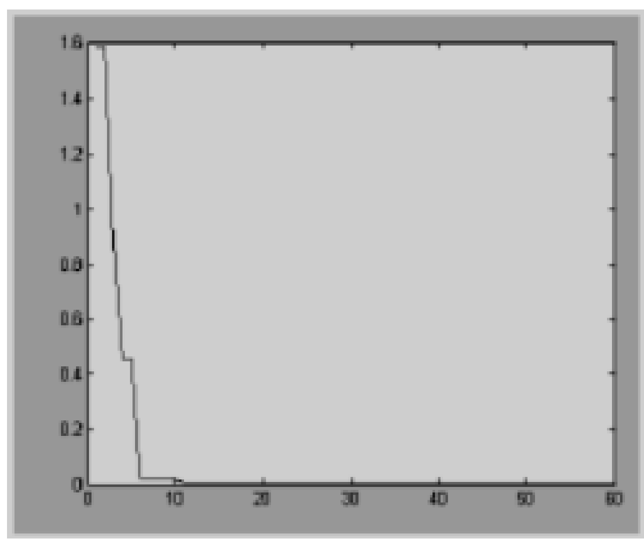

Fig. 5. Optimization convergence chart of Ackley function in standard cultural algorithm

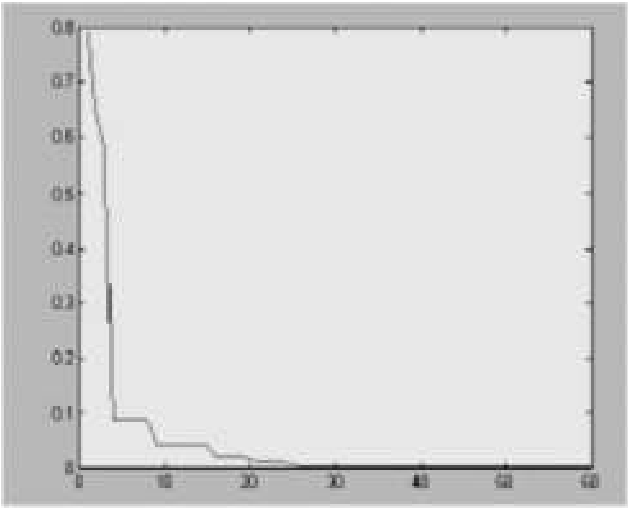

Fig. 6. Optimization convergence chart of Ackley function in PSO algorithm method

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.

REFERENCES

Azarkasb S.O., and Naderi A., 2012. Designing a Pressure Vessel Using Cultural Algorithms. In International Journal of basic and applied scientific research,**2,** (10):9807-9813.

Becerra R.L. and Coello Coello C. A., 2006. Cultured differential evolution for constrained optimization. Computer Methods in Applied Mechanics and Engineering,**195**(33-36): 4303-4322.

Chung C.J. and Reynolds R.,1998. CAEP: An Evolution-based Tool for Real-Valued Function Optimization using Cultural Algorithms. In International Journal on Artificial Intelligence Tools,**7**(3):239-292.

Coello Coello C. A. and Becerra R.L., 2002. Constrained Optimization using an Evolutionary Programming-Based Cultural Algorithm. En Ian C. Parmee (editor), Adaptive Computing in Design and Manufacture, Springer, London:317-328.

Grosan C., Abraham A. and Hassainen A. E., 2011. A line search approach for high dimensional function optimization. Telecommunication System ,**46**: 217-243.

Jin X. and Reynolds R., 1999. Using Knowledge-Based Evolutionary Computation to Solve Nonlinear Constraint Optimization Problems: a Cultural Algorithm Approach. In Congress on Evolutionary Computation, Washington, D.C., IEEE Service Center:1672-1678.

Michalewicz Z., 1995. A Survey of Constraint Handling Techniques in Evolutionary Computation Methods. In Proceedings of the 4th Annual Conference on Evolutionary Programming, The MIT Press, Cambridge, Massachusetts:135-155.

Mitchell T., 1978. Version Spaces: An Approach to Concept Learning. PhD thesis, Computer Science department, Stanford University, Stanford, California.

Nanvala H. B. and Awari G. K., 2011. Review on use of Swarm Intelligence Meta heuristics in Scheduling of FMS, International Journal of Engineering and Technology, **3**(2): 80-86.

Renfrew A. C., 1994. Dynamic Modeling in Archaeology: What, When, and Where?. In Dynamical Modeling and the Study of Change in Archaeology, Edinburgh University Press, Edinburgh, Scotland.

Reynolds R., 1994. An Introduction to Cultural Algorithms. In Proceedings of the Third Annual Conference on Evolutionary Programming, World Scientific, River Edge, New Jersey:131-139.

Reynolds R., Peng B., and Whallon R., 2005. Emergent Social Structures in Cultural Algorithms. Dept. of Computer Science, Wayne State University.