Cultural Algorithms: A Study of Concepts and Approaches

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***Abstract*—This article presents a study about cultural algorithms which are considered as a computational model of cultural evolution process. This evolution can be understood as a process of inheritance in the micro- and macro-evolutionary levels. At the first level, behavioral traits are passed on generation-to-generation by genetic operators. At the second level, individuals experience are generalized in maps, which are grouped together to form a space of beliefs of the population. A brief discussion of the potential of this sort of algorithm is presented in this paper.**

***Keywords*-Cultural algorithms; Genetic algorithms; Cultural evolution; Multi-objecive optimization.**

I. Introduction

The main purpose of this paper is to advance the study of concepts related to the integration of methodologies from artificial intelligence, cultural and genetic algorithms.

In section II are presented the basics concepts related to metaheuristic called genetic algorithm, including its operation. Still, section III talks about the Cultural Algorithms, its operation and about belief space and populational space. And finally, in section IV are made final remarks.

II. Genetic Algorithms

Genetic algorithms (GAs) are a technique of the search and optimization inspired by the Darwinian principle about the natural selection and the genetic reproduction [1]. Was invented by John Holland in the 60's and developed by students at the University of Michigan in the mid-1970s. the application of genetic algorithms was initially proposed to formally study the phenomenon of evolution, as it occurs in nature [2].

According to Charles Darwin's theory, the principle of evolution favors individuals better adapted to the environment, fostering a greater chance of longevity and reproduction. Consequently, these individuals are better adapted will have a better chance of perpetuating their genetic code in future generations. In genetic algorithms, a chromosome is a data structure that represents one of the possible solutions of the search space of the problem, the chromosomes are then subjected to a process that includes assessment, sexual selection and recombination (crossover) and mutation [3].

Genetic algorithms have also been applied to several problems optimization [4], such as combinatorial optimization of mathematical functions. It optimizes also the solution of problems related to the routine work of sales representatives or with the choice of road trips; optimization of circuit layout, distribution and business and synthesis of electronic circuits.

```
Procedure Canonical_GA
Begin
  t: = 0
  Initialize Population(t);
  Evaluate Population(t);
  Repeat
    t: = t + 1;
    Select(t) from Population(t-1);
    Crossover(t);
    Mutate(t);
    Evaluate(t);
  Until terminating condition
End
```

Figure 1. The canonical GA Pseudo Code

A. Basic Operation

Some items and terminology are important to characterize the genetic algorithms [5], [6]:

- **Gene:** Basic unit of the chromosome, each gene represents a variable or constraint of the problem.
- **Chromosome (string or individual):** Each possible solution can be defined as a sequence of characters that represent the variables of the problem.
- **Population:** Set of solutions (individuals) of the current generation.
- **Parents:** Individuals "selected" to convey their features for the new offspring (next generation).
- **Children:** New offspring, or generated by the individual "parents".
- **Temporary Population:** "Population" between generations of a GA replaces the current generation of partially or completely, as insertion model adopted new individuals.
- **Generation:** Iterations performed by the GA until the stop criterion is satisfied.

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```
Procedure Cultural_Algorithm
Begin
  t = 0;
  Initialize Population(t);
  Initialize Belief Space(t);
  Evaluate Population(t);
  t = 1;
  Repeat
    Adjust(Belief Space(t), Accept(Population(t)));
    t = t + 1;
    Select Population(t) from Population(t-1);
    Evolve Population(t);
    Evaluate Population(t);
  Until terminating condition
End
```

Figure 2. The Cultural Algorithm Pseudo Code

- **Genetic operators:** Operators inspired by nature inserted genetic diversity in the population.

After initialize the population, for each generation the genetic algorithm will select the fittest individuals all over them and apply the operators of recombination and mutation in order to generate the seed responsible for the origin of the next generation. This process will repeated on until the terminating condition is reached. A genetic algorithm in the form of pseudocode is shown in Figure 1.

III. Cultural Algorithms

Cultural Algorithms have been proposed by Robert Reynolds (1994) and are characterized by being a branch of evolutionary computation that uses a mecanism of knowledge called belief space. The cultural algorithms can be considered as an extension of genetic algorithms.

Culture is defined by [7] as a "system of symbology encoded conceptual phenomena that are historically and socially transmitted within and between populations". Still, as shown [8], "over time, humans have evolved a set of capabilities that support training, coding and transmission of cultural information".

The Cultural Algorithms as well as Genetics Algorithms are stochastic search algorithms inspired by the behavior of species in nature [9]. In contrast, cultural algorithms are based on archaeological and social theories that shape cultural evolution of the people [10]. It is believed that culture evolves over generations. And besides cultural evolution is faster than genetic evolution. This makes possible a better genetic adaptation [11].

Nowadays the research on cultural evolution is directed at two distinct levels: *micro*-evolutionary and *macro-evolutionary*. At first there is the modeling of the population itself. In the second level the knowledge obtained by members of the population over the generations is modeled. Knowledge, as codified and stored, helps guide the behavior of individuals in their populations. Another important focus is that both advocates that cultural information can be transmitted between individuals belonging to the same generation as between individuals of different generations.

A. Basic Operation

The operation of a cultural algorithm in pseudocode format can be seen in Figure 2. As described by [12], the cultural algorithms have a basic operation described from two main components: *Populational Space* and *Belief Space*.

First, individuals of populational space are evaluated through a performance function *validation()*. After this an acceptance function *accept()* determines which individuals impact on the belief space. The experiences of chosen best individuals are used to update the knowledge and beliefs of the belief space through the function *update()*. And then there is the space of beliefs is used to influence the evolution of the population, new individuals are generated from the space of beliefs.

In two ways of *feedback* mentioned above, one is responsible for managing the functions *accept()* and *influence()*, while the other creates a double-system inheritance from the individual experience and function *evaluate()* where the new population and their beliefs are generated. The population and belief space interact and support one another in a similar manner to what occurs in the evolution of human culture. The activity flow of the CA procedure can be seen in Picture 3.

B. Belief Space and Populational Space

The **populational space** is a set of solutions that can be modeled using any technique of Computational Intelligence [11] that makes use of a population of individuals. The **belief space** is where the true storage and knowledge

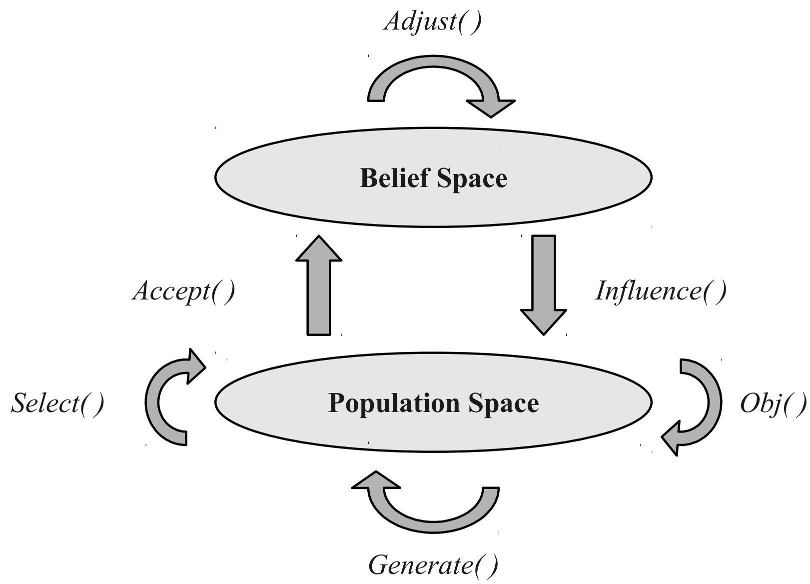

Figure 3. Basic Operation of Cultural Algorithm

representation (as the experiences or individual maps) acquired during the evolution process. It is the from the space of beliefs that individuals are guided toward the best regions of the search space.

This process can be divided into five broad categories where the cultural learning can be identified: normative, situational, domain, history and topographic knowledge. The *normative knowledge* is a set of interval variables promising provide standards for individual behavior and orientations in which individual adjustments can be made. The knowledge normative leads individuals to "jump a good track" if they already are not.

The *situational knowledge* provides a set of cases copies that are useful for the interpretation of an experience specific individual. Situational knowledge leads individuals to move to a space of examples. The *topographic knowledge* was originally proposed to serve as a standard of landscapes functional, ie, the landscape is divided into cells according with the spatial characteristics and each cell keeps track of best individual in your area.

The *domain knowledge* uses the knowledge about the domain problem to guide the search. For example, in a landscape functional, composed of cones, knowledge about the form of a cone, as well as related parameters, are useful to decide which direction to move during the search process. The *historical knowledge* monitors the process research and store the important events of this research. These important events can cause a significant change in search space or a detection of landscape changes. Individuals guided by historical knowledge, may refer to the events registered for guidance in choosing a direction of movement.

As Reynolds points with five sets of sources knowledge is possible to represent any cultural knowledge, requiring only that there is a combination of five elements. When grouped together, these five groups may show interesting collective behaviors on different roles in search process which is called **Cultural Swarm**.

There are several symbolic representations that can be used to represent the space of beliefs, including semantic networks, logic, set theory, among others. The individuals in a population are characterized by a *set of properties* or *traces*. Here, we has a trait as value taken on a hierarchically structured set, where more generally are at the root of a tree, while the more specific terms are represented by the leaves of this the tree. This designation, as Reynolds points out, can be seen as a semantic network where there is a path from the root to each term of the hierarchy.

In this assumption we have yet the possibility that exist a correlation between the hierarchies, creating prerequisites between them. In this organization there may be a tree hierarchies where some may have pre-requisites and others do not, as can be seen the example in Figure 4.

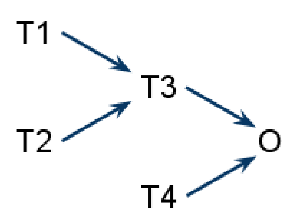

Figure 4. An example of Hierarchies in Culturam Algorithms

In Figure 4 has traces of two structures independent connected node where the "O" can be seen as a "dummy" node, since it is not a prerequisite for any other node, the

T3 node has the prerequisites T1 and T2, and the T4 node has no prerequisites, but serves as a requisites for node O. With this we have a standard structure of chromosomes of a genetic algorithm without prerequisites where all traces can be connected to the "dummy node" in a star-type structure. The set of chromosomes used to specify the individuals are used from this data structure using an algorithm that performs a sort topological structure of the pre-requisite for given traces.

IV. Conclusion

This paper presents a study on cultural algorithms considered as a computational model of a process of cultural evolution. This pattern occurs as an inheritance in microevolutionary and macroevolutionary levels. At the first level behavioral traits are passed from generation to generation by the operators. In the second level, individuals generalize their experiences on maps, which are grouped to form a space of beliefs of the population.

This discussion about the potential of this type of algorithm encourages future studies regarding the feasibility of their use in both static and dynamic environments of complex multiagent systems, tracing simulations of effective learning processes.

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