Cultural Algorithms: Concepts and Experiments

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Abstract- Evolutionary computation is a generic name given to the resolution of computational problems planned and implemented based on models of the evolutionary process. Most evolutionary algorithms proposed follow biological paradigms, and the concepts of natural selection, mutation, and reproduction. There are, however, other paradigms which may be adopted in the creation of evolutionary algorithms. Several problems involving unstructured environments may be addressed from a point of view of cultural paradigms, which offer plenty of category models where one does not know all possible solutions to the problem – a very common situation in real life. The purpose of this work is to apply the computational properties of cultural technology to the solution of a specific problem, adapted from the robotics literature. A test environment denoted *Cultural Algorithms Simulator* was developed to allow anyone to learn more about the rather unconventional characteristics of a cultural technology.

1 Introduction

The largest part of the computational problems found in the real world does not have a definite solution. This occurs when a problem is only partially known, when one does not have enough information to process it or when there is not sufficient time to solve it exactly. Curiously, live organisms have been facing these kind of problems during millions of years, finding food and sexual partners or avoiding predators and dangerous situations.

From their success or failure depends the survival of species in their ecological niches, according to the model suggested by Charles Darwin about natural selection (Desmond and Moore. 1995). One of the reasons related to the success of "selected" species is the capacity of its organisms to act according to behavioural patterns pre-established. The organisms are able, in this way, to fill out information "gaps" found in complex problems. They may "suppose" that specific variables will be behave according to a pattern, or supply information that is missing. And what kind of pattern would it be? How can the organisms reduce an action of several behaviours down to options practicable of action?

Some researchers, such as E. O. Wilson, offer a biological model of creation from innate behaviours. These behaviours would be inherited genetically and would be a result of natural selection. They would act as a "sideway" cognitive behaviour to optimise or adequate possible actions to a determinate situation. Wilson called these innate behaviours epigenetic rules (Wilson, 1999).

When we face the issue of human adaptability, however, which extrapolates its genetic conditions, we get surprised at this species' use of "strategies" of adaptation – besides genetic – and mixed types of sociability – as behaviours in a cultural system. According to the point of view of the anthropologist C. Geertz: *The culture would be better seen as a set of control mechanisms – plans, recipes, rules, and instructions (what computer engineers call "programs") – to lead the behaviour. The second idea is that the man is absolutely the most desperate animal to depend on such control mechanisms, extragenetic, out of skin, cultural programs to command its behaviour. (Geertz, 1989).*

The culture, from this point of view, would "store" categories and organise the world in such a way to create a model of conclusions, about variables objects and situations, making use of a limited number of "mental instruments". The human brain, according to Pinker (1999), would be an instrument of cognitive metaphors – a metaphoric mind that could "guess" previous knowledge obtained from prior experiences and fill in the knowledge "gaps" that permeate the problems of the real world. In this way, when faced with a new computational problem, we would have a set of useful conclusions about other similar domains, beyond the epigenetic rules suggested by Wilson. We will call this property of the culture to create general schemes for multiples domain of "common sense", or interpretative schemes of the world.

In the same way that models and concepts found in biology provided inspiration for the resolution of computational problems, new metaphors are being created connecting other knowledge areas to computer science. Researchers have been working in a gradual movement apart from the models offered by biology. Cultural Algorithms, for example, are based on the supposition that one can get better learning rates for an evolutive algorithm (such as a genetic algorithm) (Goldberg, 1998) adding to it one more element of evolutive pressure – called *beliefspace*, a mechanism of cultural pressure. This way, a system of double inheritance, both genetic and cultural, could better respond to a large number of problems.

It has been frequently suggested, however, that cultural evolution enables societies to evolve or adapt to their environments at rates that exceed that of biological evolution based upon genetic inheritance alone. (Reynolds, 1998a, 1998b).

Another research topic named Artificial Societies consists, according to N. Gilbert (1995a, 1995b), in the simulation of theories or social models expressed as computer programs. These programs have been used for tests of theories and to validate opinions that cannot be tested in the "real world". According to Gilbert, simple patterns of individual repeated actions can lead to social institutions extremely complex. The interaction between individuals (agents) would became a self-organised non-linear system.

Gessler (1999) suggests a new knowledge domain that tries to connect the models found in complex adaptive systems to the models found in the domain of culture, an undertaking that would follow a research line involving Artificial Intelligence (AI), Artificial Life (AL), Artificial Societies (AS) and would justify what the author calls Artificial Culture (AC): "*...artificial culture is a population of individual agents, with its own sense, with its own cognition and performance, interacting in a social ambient with others agents in a physical environment of artifacts and others objects*.

In view of these concepts, the central idea of this article consists, first, to consider that the culture has its own computational properties which must be treated accordingly – making use of paradigms created in the human sciences and not in the biological sciences. Second, we believe that some computational problems may benefit from a cultural method of resolution, and this can lead to automation of processes by intelligent agents. The resolution of a computational problem, in this point of view, would be an adaptive reply of a culture by agents created specially to a given domain.

Several authors wrote about a confrontation between individuals and society, and how the former can influence the letter and vice-versa. Perspectives vary from that of Emile Durkhein, for whom the individual is a complete and a total construction of its society, to those models where the genetic constitution completely leads the human behaviour, with social cultural features retaining few or almost no importance (Macy, 1998). Both perspectives are confused, claims Gilbert, because they do not consider the idea of emergency.

Gessler, when approaching Artificial Societies to cultural issues, proposes a few key concepts in elaboration of the Artificial Cultures. They are: **Time** – that can give support to the researcher flowing towards the future, the past, or in different scales according to the interest of the programmer. **Space** - that can be represented bidimensionally by a lattice. **Agents** – actors that will interact between themselves and will have behaviour aspects (how they interact in the world) and cognitive aspects (how they think). Some of these actions will be external, others will be internal in a cognitive sense. **Artifacts** – elements with which the agents can interact and exchange information.

Taking into account these concepts we can elaborate a representation of what could be described as an artificial culture of agents. In the Geertzian perspective of culture, this would be a control mechanism for the agents' behaviour. We assume that there exists a tension between the nonlinear individual will and the behaviours incentivated by the culture. For all practical purposes, the culture orients and pre-selects possible action categories for the individuals.

2 Artificial Culture and its Protocol

In this work we focus our attention on a practical problem adapted from the robotics literature: to find an object (such as a buried land mine or a missing person) in an unknown place, in an environment of unknown dimensions and populated by obstacles in unknown locations. This type of problem is commonly referred to as "goal search in an unstructured environment." It can be represented by a bidimensional lattice denoted *board* (Figure 1), where A represents the agent (robot), G and B respectively represent the goal and the obstacles (both unknown to the agent) and the numbers in the board represent the cost of experimentation of each particular cell. The objective of the cultural algorithm is to find the goal with the minimum number of steps while avoiding the obstacles.

The solution to this problem shall be given by a sequence of generations of agents, denoted *community*. The agents can only sense the cells adjacent to them, as in real robotics problems, where the sensors can only "see" at most a finite distance. The set of cells around the agent is termed *quadrant*.

1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	B	3	1	1	1
1	B	B	B	1	1	1
1	B	1	1	1	1	1
1	1	1	2	1	G	1
1	1	A	1	1	1	1

Figure 1: Bidimensional lattice board.

From the point of view of the agent, this search problem is quite complex, for it does not know where the goal is – or if it exists at all – and cannot see the world beyond its quadrant. Furthermore, it has no previous heuristics to facilitate the search.

To better understand the cultural algorithm selected to solve the search problem, we shall now introduce some basic concepts and representations of the artificial culture as it relates to the problem. These representations are abstraction levels placed between the (unknown to the agent) problem domain (the board) and the agents. The union of these abstraction levels constitute the protocol of the artificial culture – the model which relates the dynamics of the agents, the problem domain and its cultural representation.

2.1 Agents

The agents are the actors whch must experiment each cell in the board following what Freud refers to as the “pleasure principle,” according to which the agent must select the cells with smallest cost of experimentation.

2.2 Paradigm

The paradigm is the agent’s personal representation of the *beliefspace*, or its personal interpretation of the cultural references. According to Gessler, it is the agent’s cognition and its private vision of the world’s cultural interpretation. The paradigm which represents the best solution to the search problem will be denoted BestParadigm.

2.3 Beliefspace

The *beliefspace* is a collective representation of the real world. In other words, it is the real world as interpreted by a community’s culture, where agents find inference and moral values.

2.4 Board

The board is the real world, which can never be entirely known to the agent. It contains the cost of experimentation to which the agents must abide when performing the search.

2.5 Exploration

The agents, members of a community, sequentially search the board for the goal. The solution obtained by the agent who finds the goal in the smallest number of steps will be elevated to “model” of the community, or BestParadigm. According to Geertz, this model or ideology is a “diagram of social and psychological processes.” The culture will then try to orient the behavior of the new generations of agents towards this best solution. The final solution for the search problem will then be given by the sequence of motions of the agent that found the overall best number of steps.

Each agent in the community is driven by a function that makes it select cells with the least amount of displeasure. In case more than one cell in the quadrant has an equal minimum displeasure, the agent will choose one at “free will” – in this work represented by a random selection. It must be noted that the principle of pleasure has nothing to do with the global resolution strategy of the problem at the collective (cultural) level. On the contrary, it is related to the agent while an autonomous entity. The culture controls the emergent behavior to be adopted as model, creating a global action strategy – an ideology – with respect to the given problem domain.

The agent selects the cell with minimum displeasure, as indicated by the *beliefspace*. It then interferes in the *beliefspace* adding to it the cultural value, as:

$$\text{beliefspace}(x) = \text{beliefspace}(x) + \text{board}(x)$$

where x is a set of cells in the board.

In this work the functions representing the agent-culture interaction are chosen in accordance to the problem adopted. They cannot, and do not intend to establish a mathematical model of how cultural processes happen in the real world. By adopting a random function as explained above we insert, in the process, a system of multiple interactions between agent and culture. We intend to analyze other mathematical representations in our future work. For now, our focus must not steer from the main idea, which is to produce an artificial culture compatible with the problem addressed. We do not attempt here to recreate or reproduce the technological culture employed by human beings in all its complexity and diversity.

The pseudo-code of the cultural algorithm described above is shown in the sequel.

2.6 CAS Pseudo-Codes

Individual Search

```
number of steps = 0;
while (goal not found) or (number of steps < number of
      steps in BestParadigm) do
    {
    agent alters quadrant according to

        beliefspace(quadrant) = beliefspace(quadrant) +
                                board(quadrant)

    agent transfers data from quadrant found in
        beliefspace to its own paradigm
    agent selects among the options in beliefspace which
        is its next position in board
    agent moves to next position and increments number
        of steps
    }
```

Cultural (Paradigm) Change

```
if (number of steps in paradigm < number of steps in
      BestParadigm) do
    {
    BestParadigm = paradigm

    beliefspace(BestParadigm) = 0
    generation is incremented
    a new generation of agents is initiated
    }
```

In the cultural change algorithm, the cells of *beliefspace* belonging to BestParadigm are zeroed to represent the fact that the culture increases the amount of pleasure associated with those cells, giving an incentive to the behavior associated with BestParadigm.

3 Cultural Algorithms Simulator

To test and vallidate the theoretical concepts presented above we developed the CAS, Cultural Algorithms Simulator. While initially our intention was solely to provide make available an enviroment for analysis and experimentation, we soon realized that we were dealing with a class of systems totally different from what we were used to.

Systems normally utilize well established algorithms with relatively fixed procedures – at least this is what most people expect from them. With evolutionary algorithms, on the other hand, it becomes much more difficult to understand the peculiarities of each solution. Even when the system has a precise answer, the solution obtained can almost never be exactly duplicated. This property of evolutionary algorithms in general, and of cultural algorithms in particular, has been little explored or discussed in the literature. The creation of systems with an individuality, or "soul," shall be given more attention in our future work.

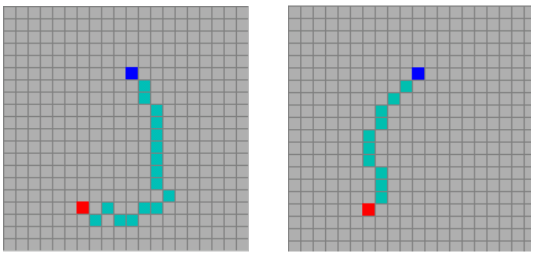
The development of CAS is based on our wish to share an intuitive understanding about the treatment of a new class of systems, individuals capable of unexpected creativity, typical of live beings.

CAS is presented in Figure 2 (at the last page of the article) and can be accessed on the Internet at www.geocities.com/belfra2000. The user is able to select the agent's starting point and goal, the location of the obstacles, and the ammount of displeasure associated to each cell of the board.

4 Experiments

In this section we report on the experiments performed with CAS. We hope to contribute in the sense of making evident the importance of creating a new methodology for testing and analysing the results obtained. This is not a trivial task, for the diversity of behaviors of the solutions provided by CAS resemble more a descriptive anthropology rather than a simple software test.

In the first experiment we compared the performance of 20 communities of 50 agents each to 20 communities of 500 agents each. The start and goal points are as shown in Figure 3. The optimal number of steps from start to goal is equal to 11. Tables 1 and 2 present the summary of the results obtained, showing the best number of steps for each community, the agent which achieved best performance within the community, the number of paradigm changes, and the total running time in miliseconds.



(a) (b)

Figure 3: Experiment #1. (a) A solution with 50 agents; (b) A solution with 500 agents.

Comunity	BestSteps	BestAgent	ParadChanges	Time
1	11	13	5	13020
2	15	28	3	16420
3	19	22	3	15050
4	14	33	6	13950
5	11	9	2	12570
6	13	20	8	18400
7	11	43	2	14450
8	13	12	6	14990
9	12	41	5	16860
10	18	40	7	15600
11	17	6	2	16810
12	15	15	5	14170
13	17	31	6	15330
14	19	12	5	15430
15	14	44	3	15870
16	12	7	4	14940
17	15	15	3	13950
18	11	15	1	14940
19	15	14	5	16420
20	14	31	4	14170
Average	**14,3**	**22,55**	**4,25**	**15167**
Std Dev	**2,637782**	**12,7092**	**1,860249**	**1393,629**

Table 1: Results of experiment #1 with 50 agents.

Comunity	BestSteps	BestAgent	ParadChanges	Time
1	18	348	5	148790
2	14	55	8	148850
3	11	22	7	134120
4	13	67	6	148680
5	11	28	4	138250
6	14	112	3	143024
7	14	109	7	147310
8	14	84	3	141710
9	13	18	6	182290
10	11	48	3	138030
11	11	30	2	136050
12	15	261	10	145500
13	11	390	5	135500
14	12	20	7	132590
15	11	71	8	141980
16	16	134	6	208770
17	12	116	4	137040
18	12	309	6	149180
19	15	89	9	147030
20	13	224	8	147910
Average	**13,05**	**126,75**	**5,85**	**147630,2**
Std Dev	**1,959457**	**115,6755**	**2,207046**	**17801,93**

Table 2: Results of experiment #1 with 500 agents.

One of the most interesting characteristics observed in this experiment is the diversity of cultural patterns established by each community. Even for the solutions with the same number of steps, the resulting *beliefspace* is entirely different (one such *beliefpace* is shown in Figure 4). The structuring scenarios atained by the agents cannot be reproduced in general, belonging to a given instant in time and space. They represent a unique and precious adaptive behavior which solves a computational problem following a complex chain of relationships. The configurations generated can be metaphorically related to the behavioral knowledge of the community with respect to the search problem, or a tradition which emerges from the experience and which belongs to the dynamics of the process.

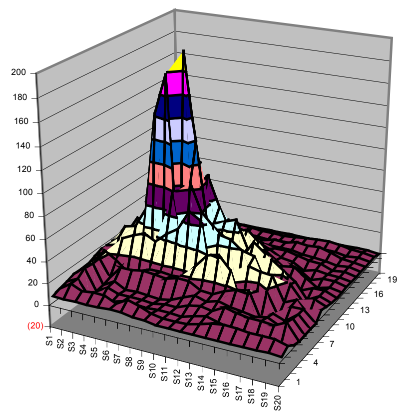


Figure 4: Cultural configuration (*beliefspace*) of the first community of 50 agents.

Compared to the 50 agents community, the 500 agents one obtained a better performance in terms of the average number of steps from start to goal (13.05 vs. 14.30 – see Figure 5), as well as a smaller standard deviation (1.96 vs. 2.64). It also had a greater average number of paradigm changes (5,85 vs. 4,25), which indicates that even the "dumbest" generations, which explored less interesting parts of the board, were able to optimize their search to attain better results.

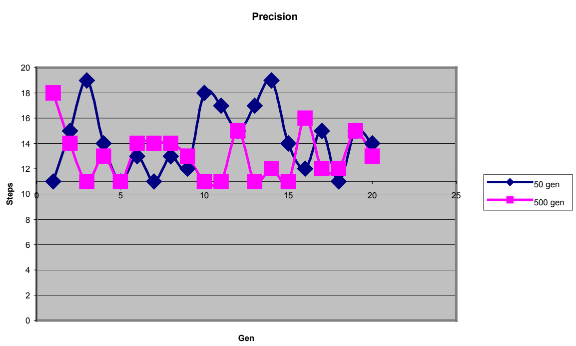
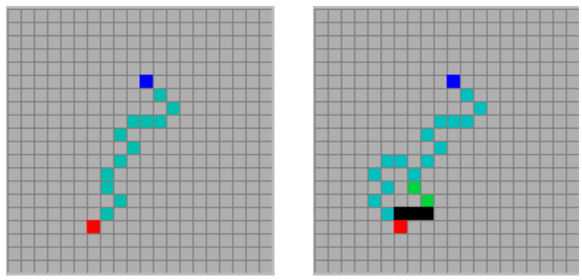


Figure 5: Number of steps for each community in experiment #1.

In the second experiment we considered the same scenario as in experiment #1, except that, after obtaining a solution with a community of 50 agents, we blocked three cells close to the goal and started a new community of 500 agents. The new community is aware of the pevious cultural configuration but must take into account the new scenario. The comparison between both solutions is not immediate, since they attend to different problems. The paths are shown in Figure 6.



(a) (b)

Figure 6: Experiment #2 (adaptation). (a) 50 agents without obstacles. (b) 500 agents with obstacles.

In this experiment, it was surprising to see how the 500 agents community initially utilized the solutions offered by the 50 agents one, whenever these solutions were close to the optimum, instead of finding whole new solutions. This results makes evident the conservation of a global action strategy which regulates the agents. It can be metaphorically compared to the concept of culture of the authors mentioned in the Introduction.

Figure 7 presents the best number of steps for the first 20 agents of both communities and the percentage of cells belonging to both solutions (variable *inter*). As one can see, the second community tends to utilize more cells of the first one whenever the former attains better results than the latter, or when both attain the same result and this is close to optimum.

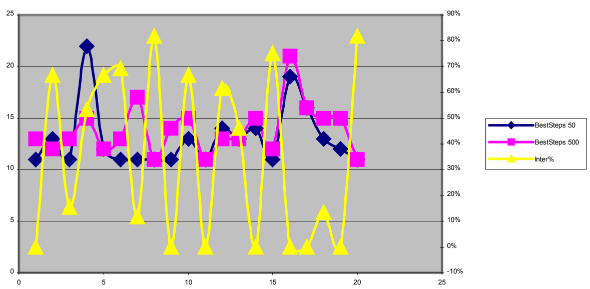


Figure 7: Number of steps for each community in experiment #2.

5 Conclusion

Cultural algorithms offer a powerful alternative for search problems. They can also provide an understanding of cultural phenomena, and the underlying tehnology utilized by the human species. This technology leads us to reflect on the possibility of generation of an experimental knowledge, created by a community of agents in a given domain.

To what degree this knowledge is cognitive for the community of agents is a theme for future work. The answer may be similar to that involved in the hard task of communication between two different cultures. The specificity of each artificial culture appears to be a counterpoint to traditional digital systems, characterized by a large reproductibility, and devoided of the concepts of original or copy. On the contrary, the technological culture implies in a singular individuality of each system, completely different from today's industrial standards. A new software engineering that can deal with these systems is still far in the horizon, in much the same way that we still lack methods to understand the great arts.

Acknowledgments

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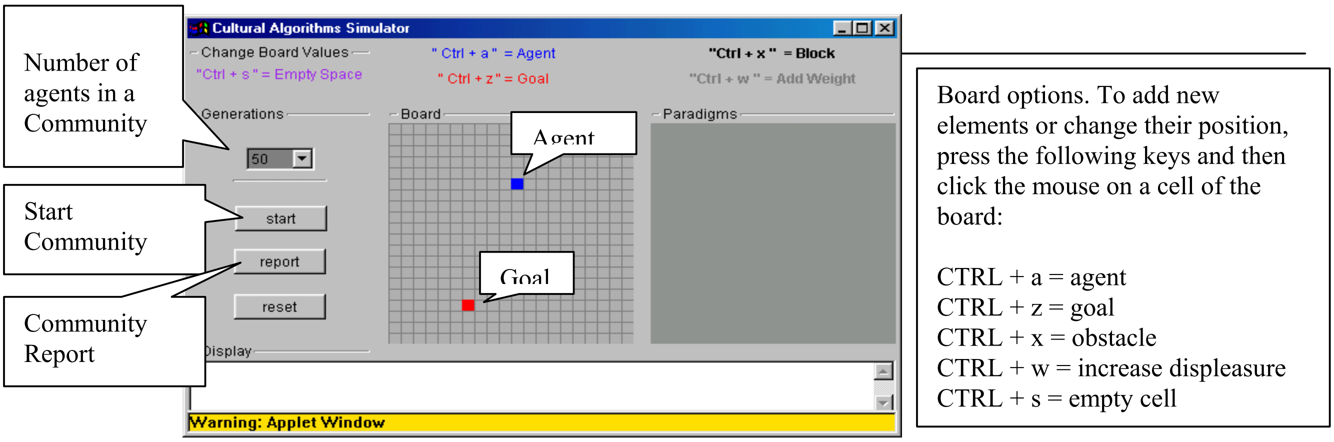

Figure 2: Cultural Algorithms Simulator.