Evolving Heterogeneous Social Fabrics for the Solution of Real Valued Optimization Problems Using Cultural Algorithms

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Abstract—A question of interest to those studying the emergence of social systems is the extent to which their organizational structure reflects the structures of the problems that are presented to them. In a recent study [14] used Cultural Algorithms as a framework in which to empirically address this and related questions. There, a problem generator based upon Langton’s model of complexity was used to produce multi-dimensional real-valued problem landscapes of varying complexities. Various homogeneous social networks were then tested against the range of problems to see whether certain homogeneous networks were better at distributing problem solving knowledge from the Belief Space to individuals in the population. The experiments suggested that different network structures worked better in the distribution of knowledge for some optimization problems than others. If this is the case, then in a situation where several different problems are presented to a group, they may wish to utilize more than one network to solve them. In this paper, we investigate the advantages of utilizing a heterogeneous network over a suite of different problem.

I. INTRODUCTION

One key question of interest to those studying the emergence of social systems is the extent to which their organizational structure reflects the structures of the problems that are presented to them. Specifically, does the structure of a social or organizational network facilitate the exchange of information needed by a group to solve a problem?

In a recent study [14] used Cultural Algorithms as a framework in which to empirically address this and related questions. There, a problem generator based upon Langton’s model of complexity was used to produce multi-dimensional real-valued problem landscapes of varying complexities. Various homogeneous social networks were then tested against the range of problems to see whether certain homogeneous networks were better at distributing problem solving knowledge from the Belief Space to individuals in the population.

The experiments suggested that different network structures worked better in the distribution of knowledge for some optimization problems than for others. If this is the case, then in a situation where several different problems are presented to a group, they may wish to utilize more than one network to solve them. In this paper, we investigate the advantages of utilizing a heterogeneous network over a suite of different problem.

II. THE CULTURAL ALGORITHMS FRAMEWORK

The Cultural Algorithm (CA) is an evolutionary computation model derived from conceptual models of the Cultural Evolutionary process [9] [10]. The population, belief space, and communication protocol between the population and the belief space are the three major components of this model, as shown in Fig. 1. The population can support any based computational model, such as Multi-Agent Systems, Genetic Algorithms, and evolutionary programming.

In the earliest Cultural Algorithm only one knowledge source (situational knowledge) was used [3]. Next, in [1], Reynolds and Saleem introduced other knowledge sources...
into the belief space; situational, normative, topographic, domain, and finally history knowledge. The situational knowledge keeps track of the individual who did the best behavior in the population. The normative knowledge provides standards for individual behaviors to ensure that individual still within the scope of the system. The domain knowledge contains the sequence behaviors of the best individuals in the population. The history knowledge is useful in dynamic environment to store all changes in the problem landscape, such as the direction of the population behaviors either towards convergence or divergence. The topographical knowledge maintains a multi-dimensional grid representation of the population space to force the enhancing in the weak areas.

The basic pseudo-code of the Cultural Algorithm is shown in Fig. 2, where P(t) represents the population at time t and B(t) for the belief space at time t. At the end of each iteration, individuals in the population space are evaluated using the performance function, Obj(). Then the acceptance function, accept(), is used the select the appropriate individuals to update the Belief Space. The acceptance function selects the best elements to update, but in some cases the acceptance function selects from different categories to explore all results of the population. Updating the Belief Space occurs via the update() function. In the Belief Space, there are many kinds of knowledge sources. Some sources are updated by the update function and some of them by the interaction with other updated sources. Next, the influence function transmits the knowledge from the belief space to the individuals in the population, influence(). The accept() and influence() functions form the communication protocol between the belief space and population.

The Cultural Algorithms repeatedly produces a new generation and update the belief space until the termination condition is satisfied. The Cultural Algorithms is flexible since it can run in short-term and long-term applications and in static and dynamic environments. The termination condition may depend on the population convergence or divergence. It may depend on constant and variable number of iterations.

### III. THE SOCIAL FABRIC

Saleem [13] started integration of all knowledge sources into the Cultural Algorithm framework. He developed the CADE, the Cultural Algorithm for Dynamic Environment, to track the changes in the dynamic environment and store them in the Belief Space. He added the History and the Domain knowledge sources to the Belief Space. History knowledge allowed reasoning about time, while the Domain knowledge allowed reasoning about the individuals’ direction and magnitude. He identified the required structure for each knowledge source in the Belief Space to find and track the changes in the dynamic environment.

Saleem’s approach was applied to the solution of problems in the Cones World environment, where the problem was to find the highest peak in a multi-dimensional landscape, where the peaks are moving over time. The Cones World environment was generated via a benchmark problem generator developed by [6] and called DF1 in their work. Fig. 3 shows a 3D example of the Cones World environment. The random selection of the knowledge sources was the foundation of Saleem’s integration function.
Next, Peng [12] used the Marginal Value Theorem (MVT) [2] to integrate the knowledge sources of the Belief Space in order to guide the problem solving process. It had been shown in foraging theory that the Marginal Value Theorem can optimize the energy intake of predator/foragers within an environment. The main idea had been taken from ecology; the habitat resources would be decreased over time if the foragers resided too long within the habitat’s borders. Thus, the forager stays within the habitat until the resources become less than the average expected value.

Peng observed at each time step that the individuals generated by each knowledge source using a normal distribution could be described by a “boundary box” or a patch with a given central tendency and standard deviation. For example, in Fig. 4 notice the shifting of the patch for situational knowledge from one place on the landscape to another. In fact, the original patch orientation is rotated and then translated towards the optimal point “+” over time by the knowledge source update process.

Each of the knowledge sources can be viewed as a predator. Each knowledge source (predator) controls the placement of individuals on the landscape to exploit the available resource (prey). If the average performance of those individuals controlled by knowledge source (predator) falls below the population average, the bounding box will be adjusted to increase the performance.

Peng modified the roulette wheel to emulate the action of the energy intake function. The size of a knowledge sources area under the wheel reflects its ability to exploit above population average gains. At every time step, each of the individuals in the population is influenced by one of the knowledge sources based upon the spin of the wheel. Then, the individual moves into the bounding box of the selected knowledge source.

In Peng’s version, individuals acted independently and were influenced by a single knowledge source [12]. Ali [1] added the social fabric into the Cultural Algorithm framework to allow the interaction between the individuals so as to: give the individuals the ability of making decisions as to which knowledge source they will follow; identify the minimum social structure needed to solve problems of certain complexities; and investigate how the knowledge sources influence the individuals through a social network. Ali used a fixed topology to connect the individuals with their neighbors. The topology was kept constant throughout the optimization process, but the assigned to the network nodes were randomly reshuffled each time step. Ali proved that just having a social fabric to distribute influence in the population space was sufficient to improve performance of the influence function in the Cultural algorithm.

Ali viewed the social fabric as a weaving process. The concept is illustrated schematically in Fig. 5. In the figure, there are five different networks where each is given as color-coded vertical lines, one for each of the five knowledge sources. Individuals are given as horizontal lines with a node representing a possible participation in each network. The node is blank, darkened, or darkened-circled. The node is blank if the individual does not participate in that particular network. It is darkened and colored the same color as the network if it participates sometimes. It is darkened-circled if it participates frequently. In the figure, the five individuals are ordered from highest participation to lowest participation of the five networks.

Ali’s main contribution was adding the social fabric into the Cultural Algorithm. The interconnections between the individuals in the population can be viewed as a social fabric, created by the interactions between the individual. Fig. 6 shows how the social fabric component is embedded into the Cultural Algorithm framework.
are 5 knowledge sources: KS1, KS2, KS3, KS4, and KS5 that correspond to the five knowledge sources in the Belief Space. Every Knowledge source is color coded and its color is given to the individual that will be influence at that time step.

Figure 5. Social Fabric

In Figure 6, there are three perpendicular dotted lines point to three individuals with a complete set of neighbors. Each individual has four neighbors to interact with, so this topology named square topology. Ali used three other homogeneous topologies: Ring (lbest), Square, and Global (gbest) topologies[1]. Fig. 7 shows the three topologies. The topologies differ from each other by the number of neighbors connected to each individual or what called the degree.

Figure 6. Embedded Social Fabric component in CAT

At each time step, every individual is influenced by one of the knowledge sources. Knowledge Sources do not know anything about the network and the selected individuals’ position in it and vice versa. This is a double blind process. The individual then transmits the name of the influencing Knowledge Source to its neighbors through as many hops as specified. Next, each node counts up the number of Knowledge source bids that it collects. It will have the direct influence from the Knowledge Source that selected it, plus the ID’s of the Knowledge Sources transmitted to it by its neighbors. The Knowledge Source that has the most votes is the winner and will direct the individual for that time step. This schema called majority winning schema” [11].

Other conflict resolution approaches are: direct, least frequently used, most frequently used, and random resolution. Suppose K is the knowledge source with the most votes from all the ones in individual’s neighborhood, and L is the knowledge source from the belief space. In direct resolution, K = L. In LFU resolution, K = the knowledge source recorded the least often from the beginning of the run. In MFU resolution, K = the knowledge source recorded the most often from the beginning of the run. In random resolution, the resultant Knowledge Source is a randomly chosen one from the five knowledge sources.

Che [14] added three more homogeneous topologies to investigate in detail how a topology will impact the optimization performance: hexagon, octagon, and hexadecagon (16-gon). In the hexagon, every individual (node) interacts with exactly six neighbors see Fig. 8.a. Each individual in octagon communicates with eight neighbors see Fig. 8.b. In the 16-gon, each individual communicates with sixteen neighbors.

There are many ways to build the neighborhood topology [5][4][7]. Che gave each individual an ID. The IDs range was from 1 to n, where n is the population size. Each individual has m neighbors and marked with ID k, so the neighbors IDs will be \((n + k - m/2) \mod n, (n + k - m/2 + 1) \mod n, ..., k, (k+1) \mod n, (k+2) \mod n, ..., (k+m/2) \mod n\). Octagon example is given in Fig. 9.
Che [14] also employed a weighted incentive based majority win scheme. It is based on a Vector Voting model employed in the earliest version of Cultural Algorithms by Reynolds [9]. An example of weighted majority winning schema with octagon topology is given in Fig. 10. In the example, A0, A1… A7 and A8 are the individuals. A0 is the one deciding which knowledge source to follow. A1… A7 and A8 are the neighbors of agent A0. S, N, D, T, and H represent the situational, normative, domain, topographical, and history knowledge respectively. From Fig. 10, Agent A has the following votes:

- Neighbors A1 and A6 voted for Situational knowledge S (S repeated 2 times).
- Neighbors A2, A4, and A8 voted for Normative knowledge N (N repeated 3 times).
- Belief Space and neighbor A7 voted for Domain knowledge D (D repeated 2 times).
- A3 voted for Topographical knowledge (T repeated 1 time).
- A5 voted for History knowledge H (H repeated 1 time).

In Peng’s influence function, A0 will follow the knowledge source been selected by the belief space, so it would be the domain knowledge as shown in Fig. 10. The normative knowledge repeated the most (3 times), so A0 will follow it in Ali’s influence function as shown in Fig. 12. Fig. 11 gives the average fitness of each knowledge source in the population space. Knowledge source fitness affects the individuals’ making decision. In Che’s influence function, A0 would follow the situational knowledge even if the normative knowledge occurred more frequently. The weighted majority win uses the knowledge sources as vectors in the vector voting approach. The average fitness of the current generation is the key to winning in this bidding game. If a less frequently used knowledge source finds a good solution its
average performance can increase noticeably and magnify its influence in the population space.

Figure 12. Un-weighted majority Win in Belief Space.

Figure 13. Weighted Majority Win in Belief Space.

IV. HETEROGENEOUS TOPOLOGY

In this section the mechanism for evolving the appropriate heterogeneous structure for a given problem is described. The approach uses the six homogeneous topologies (Ibest, square, hexagon, octagon, hexa-decagon and global) that were used before with the social fabricated population space in CAT2.0, as shown in Fig. 14. In the previous system, CAT 2.0, a topology was selected to be used for the entire run as shown in step 1. Next in each generation the Knowledge source wheel is spun for each individual in order to select the knowledge source that will be the direct influence of that individual in that generation. The area under the wheel is the average performance of each KS for the previous generations. The direct influences are then distributed to the agents in step 3 along with the direct influences of its neighbors in the topology. Next, in step four the weighted majority conflict resolution rule is used to determine which KS will actually influence the individual in that generation.

Fig. 15 demonstrates how the process has been changed for the new version. Step 1 reflects the selection of one of the fixed topologies for use in a generation based upon the previous performance of each topology using a roulette wheel approach. The area under the wheel for each topology is its normalized average performance in the previous generation. The selected topology is then embedded into the population space for that generation in step 2. Then for each topology there is a separate wheel shown in step 3 which is used to select the knowledge source used to influence each individual based upon the past performance of the knowledge sources for the selected topology. Thus, there are five separate KS wheels, one for each topology that is used for a generation. This wheel is used in step 4 to generate the direct influence for each individual in the population and collect the direct influence knowledge sources for its neighbors. In step 5 the weighted majority win conflict resolution rules is used to determine the winning KS for each individual. The individuals are then modified and evaluated. The results are used to update the selection wheels and the process starts again for the next generation.

Figure 14. CAT2.0 topology model.

In this paper, we will use the Cones World to see how the heterogeneous social fabric can solve evolutionary problem and to compare our results with previous work used the same experiment environment. The evolutionary problems will be generated randomly of arbitrary complexities. Peng [8][12], Ali [1], and Che [14] used the Cones World before and therefore our results can be easily compared with theirs using this test bed.

Langton developed a model of a performance landscape described as a superimposed collection of cones, the Cones World. One of the parameters of the model Langton [5], A, value reflected the entropy of the system. Increasing A will lead to unpredictable system, In other word, A value
reflexes the system complexity. We picked $A = 1.01$, 3.35 and 3.99 for our test environment complexity. $A = 1.01$ represents Fixed complexity class. The fixed complexity class will allow only the height on the cones to change. $A = 3.35$ represents Periodic complexity class. The height and the slope of the cones will change together to make the Cones World more complicated. $A = 3.99$ represents chaotic complexity classes and the system will be unpredictable. In this case, the height, slope, and the location of the cone will change over time making the landscape very dynamic and unpredictable.

Figure 15. CAT 3.0 topology model.

V. RESULTS AND ANALYSIS

In this section we compare the use of heterogeneous topologies with the homogeneous topologies for the social fabric in terms of their relative performance and their effect on the knowledge sources within the three complexity categories (fixed, periodic, and chaotic categories).

Each Complexity (1.01, 3.35, 3.99) has five randomly generated example Landscapes. We use heterogeneous topology suite that consists of 6 Topologies: Lbest, Square, Hexagon, Octagon, Hexa-decagon, and Gbest. For each landscape/topology combination 10 runs were performed on each of the 5 landscapes. So each complexity has a total of 50 runs. The maximum number of generations for each run is 500.

For the fixed category of problems ($\alpha = 1.01$), Table I, the homogeneous topologies approach fared better than the heterogeneous approach. The heterogeneous topology had the fewest 58% number of solved problems, the greatest number of generation used on overall average, and the greatest standard deviation relative to the 50 runs. But the heterogeneous topology used the fewest number of generations in producing the solved problems, and the least maximum number of generations in producing the solved problems. So, for static problems with fixed cone distribution parameters the homogeneous topologies were the most effective in solving them. On the occasion that the problem had features that supported the heterogeneous approach, that approach solved that problem effectively. However, the number of such problems constituted approximately 60% of the total number of runs.

TABLE I: THE PERFORMANCE COMPARISON OF THE SOCIAL FABRIC TOPOLOGY FOR $A = 1.01$

<table>
<thead>
<tr>
<th>Topology</th>
<th># of Runs</th>
<th>Overall Mean Generation Used</th>
<th>Std. Deviation</th>
<th># of Runs w/ Solution Found</th>
<th>Minimum Generation Used</th>
<th>Runs w/ Solution Found Maximum Generation Used</th>
<th>Runs w/ Solution Found Mean Generation Used</th>
<th>Std. Deviation</th>
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<tbody>
<tr>
<td>LBest</td>
<td>50</td>
<td>224</td>
<td>168</td>
<td>11</td>
<td>339</td>
<td>137</td>
<td>72</td>
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<tr>
<td>square</td>
<td>50</td>
<td>213</td>
<td>152</td>
<td>9</td>
<td>358</td>
<td>158</td>
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<td></td>
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<tr>
<td>Hexagon</td>
<td>50</td>
<td>229</td>
<td>169</td>
<td>40</td>
<td>491</td>
<td>161</td>
<td>112</td>
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</tr>
<tr>
<td>Octagon</td>
<td>50</td>
<td>243</td>
<td>175</td>
<td>7</td>
<td>426</td>
<td>152</td>
<td>99</td>
<td></td>
</tr>
<tr>
<td>16-gon</td>
<td>50</td>
<td>219</td>
<td>160</td>
<td>41</td>
<td>477</td>
<td>158</td>
<td>100</td>
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</tr>
<tr>
<td>global</td>
<td>50</td>
<td>238</td>
<td>186</td>
<td>35</td>
<td>361</td>
<td>126</td>
<td>83</td>
<td></td>
</tr>
<tr>
<td>Heterog</td>
<td>50</td>
<td>270</td>
<td>206</td>
<td>12</td>
<td>264</td>
<td>104</td>
<td>81</td>
<td></td>
</tr>
</tbody>
</table>

For the periodic category of problems ($\alpha = 3.35$), Table II, the heterogeneous topology had the highest 84% number of solved problems and the lowest number of generations used in all 50 runs. It used the fewest number of generations in producing the solved problems. 6 generations used to produce one of the solved problems was the lowest number of generation of the three complexity classes. The octagon topology was the closest one to the heterogeneous’ performance.

This class is characterized by the essential superposition of multiple static classes. Therefore, it makes sense that the heterogeneous approach that interweaves of subset of
homogeneous topologies will be a good fit for problems like this.

For the chaotic category of problems (alpha = 3.99), Table III, the heterogeneous topology had the highest 74% number of solved problems and the lowest number of generations used in all 50 runs. It used the fewest number of generations in producing the solved problems. It had the minimum number of generation used to produce one of the solved problems. The standard deviation was the highest relative to the 50 runs and found solution runs. Thus, the heterogeneous topology is the fastest in solving the problems. The octagon and the global topologies were the closest one to the heterogeneous’ performance.

VI. CONCLUSION

In this paper, we compared the heterogeneous topology with the homogeneous topologies. For static problems with predictable patterns of distribution, the homogeneous networks were the most effective. As more and more static problems were blended together to increase complexity, the heterogeneous approach became dominant. This was because there was work for more than one topology to perform. Our approach effectively allowed a team of networks to work on the problem space, each exploiting those patterns most suited for it. In future work we will examine exactly what properties attract the homogeneous networks to a distribution and how they can collaborate on a blended mix of distributions.

TABLE III: THE PERFORMANCE COMPARISON OF THE SOCIAL FABRIC TOPOLOGY FOR A = 3.99

<table>
<thead>
<tr>
<th>Topology</th>
<th># of Total Runs</th>
<th>Overall Mean Generation Used</th>
<th>Std. Deviation</th>
<th># of Runs w/ Solution Found</th>
<th>Minimum Generation Used</th>
<th>Runs w/ Solution Found</th>
<th>Maximum Generation Used</th>
<th>Runs w/ Solution Found</th>
<th>Mean Generation Used</th>
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<tr>
<td>16-gon</td>
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<td>10</td>
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VII. REFERENCES


