Improving Robustness in Social Fabric-based Cultural Algorithms

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Master Thesis Defence

Outline

What is Evolutionary Computation(EC)?

Evolutionary Computation

An abstraction from the concepts of biological evolution and social interactions that is used to create optimization algorithms or methodologies that are used to solve problems. [Eiben and Smith, 2003] EC algorithms are natural-inspired, population-based, iterational and utilize step-by-step improvement approaches.

- Genetic Algorithm
- Cultural Algorithms
- Particle Swarm Optimization
- Ant Colony Optimization

Robustness

Robustness in Evolutionary Algorithms

- The ability to address a vast range of problems with particular qualities with a minimum number of adjustments.
- Self-organized algorithms can learn and adapt themselves to different search landscapes.
- Such strategies improve robustness in population-based algorithms.

Social Fabric

- Social Fabric was proposed by [Ali, 2008]
- The Social Fabric is a dynamic information skin created by the agents interactions in a social context.
- These dynamic formations control the topology and type of interactions in the dynamic social sculpture. [Reynolds and Ali, 2008]
- Social interactions between individuals are modeled using an undirected graph $G(V; E)$ [Sterling, 2004].
- In this research work, The Social Fabric approach is used to improve the search behavior of evolutionary algorithms in multi-dimensional search spaces.

Research Motivation

Optimization Problems

- CEC-2015 expensive optimization problem set is used to evaluate the proposed approaches. [Chen et al., 2014]
- It is a set of 15 real-world numerical optimization problems that was used in IEEE-CEC2015 and 2016 competitions on testing evolutionary algorithms.
- Because of their high dimensionality, multimodality, and copious local optima, they are suitable to inspect and compare the capabilities of evolutionary algorithms regarding robustness, scalability, adaptability, etc.

Reasearch Goals

- In this research work, I am going to improve Cultural Algorithms from three aspects:
- Applying PSO algorithm to current Social Fabric based CAs.
- Introducing a Heterogenous Neighborhood Restructuring operator to increase the level of diversity.
- Improving the robustness of the Belief Space by introducing a Confidence-based knowledge source inspired from Statistics.
- For the comparison purpose, I am going to use CEC2015 benchmark optimization functions to compare my proposed approaches against already proposed algorithms.

Related Works I

- [Ali, 2008] introduced the idea of Social Fabric as a new influence function in CA by deploying a social network between individuals.
- [Che et al., 2010] replaced the traditional idea of roulette wheel with the vector voting model to determine the controller KS in each iteration.
- [Ali et al., 2012] introduced the neighborhood restructuring in Social Fabric with a two-layered multi-population CA model.
- [Chen et al., 2006] introduced Tribe-PSO algorithm as a multi-tribe population-based algorithm to utilize the parallel nature of evolutionary algorithms.

Related Works II

- [De Oca et al., 2009] investigates different types of heterogeneity in PSO algorithm in three categories: neighborhood, update rule and parameters.
- [Ali et al., 2016] gives a detailed description of Social Fabric based MPCA with neighborhood restructuring. It, also, proves its optimality against different optimization algorithms based on an extended benchmark testbed.

Biologically inspired algorithms

- Biologically inspired algorithms try to mimic biological evolution process. [Man et al., 2012]
- They comprise of a population of candidate solutions or individuals. Each individual is characterized by a set of genotypes or chromosomes.
- Evolutionary operators are used to evolving the individuals such as Crossover(exploitation) and Mutation(exploration).
- In each iteration of these algorithms, a new population is generated through applying evolutionary operators on individuals of a generation.

- Genetic Algorithm
- Evolutionary Programming
- Genetic Programming

Socially inspired algorithms

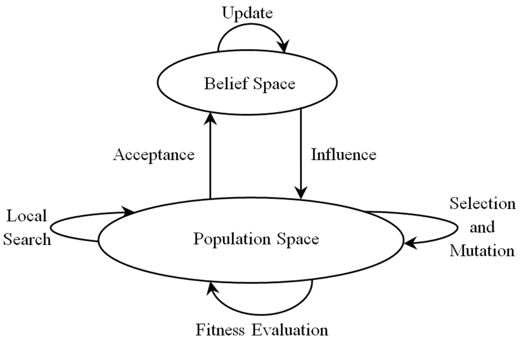
Swarm Intelligence

[Kennedy et al., 2001] Socially inspired algorithms(Swarm Intelligence) utilize a population of semi-rational agents(rather than dumb individuals) that have the ability to perceive their surrounding environment and cooperate with other agents in a self-organized manner.
Cooperation happens through communication. The agents communicate in two general ways: Direct and Indirect.

- Cultural Algorithms(CA) [Reynolds, 1994]
- Particle Swarm Optimization(PSO) [Clerc, 2010]
- Ant Colony Optmization(ACO) [Dorigo et al., 2006]

Cultural Algorithms

Cultural algorithms are a sort of socially motivated methods which combine biological evolution with socio cognitive concepts to give an optimization method based on dual inheritance theory. CAs are composed of three components: Population space, Belief space and Communication protocol.



Cultural Algorithms

```
Begin
 t = 0;
 initialize B^t, P^t
 repeat
    evaluate P^t   {obj()}
    update(B^t, accept(P^t))
    generate(P^t, influence(B^t))
    t = t + 1;
    select P^t from P^(t-1)
 until(termination condition achieved)
End
```

Figure: Cultural Algorithms

In the population-space of CA any population-based algorithm such as GA, EP, PSO, etc. could be used.

Cultural Algorithms

Belief Space

There are five types of knowledge sources in Belief Space. The elite members of Population space are selected and sent to the Belief space to extract and utilize their knowledge through the search process. [Reynolds et al., 2010]

- Situational Knowledge
- Normative Knowledge
- Topographic Knowledge
- Domain Knowledge
- Historical Knowledge

Cultural Algorithms

Knowledge Sources

- Situational: The goal of situational knowledge is to collect information from elite individuals and attempt to evolve potential solutions with this information.
- Normative: It is represented as a set of *n* intervals, and each describes a promising range of good or socially acceptable solutions for each of *n* dimensions.

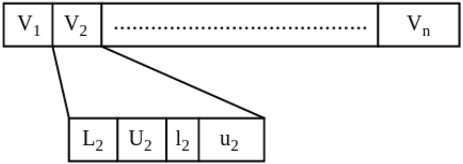
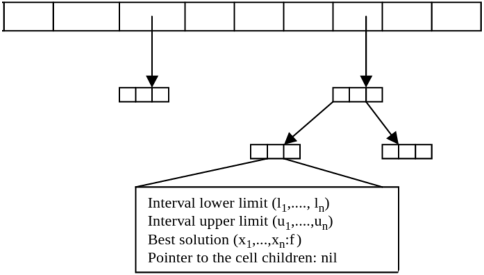


Figure: Normative KS

Cultural Algorithms

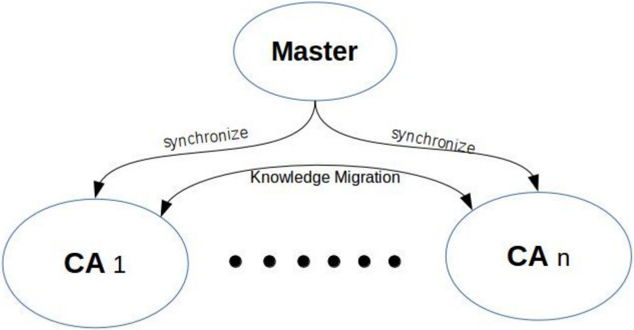
Knowledge Sources

- Topographic: It divides the whole landscape into cells and keeps track of the best individual in each cell. This KS is used to split the current search regions into subregions along each dimension of the problem. Each area will be divided into two new subregions in each generation of the optimization process.



Multi-population CA

- Multi-population CAs utilize the parallel nature of evolutionary algorithms. [Guo et al., 2011]
- It comprises of multiple CAs that run independently.
- It could be heterogeneous which means any population might have different initial parameters. [Kobti et al., 2013]



Social Fabric

Social Fabric based CA

- In this model of CA, knowledge sources are allowed to influence the population through a network.
- Individuals might be participating in different networks which might support several layers of such networks in a hierarchical manner.
- The interplay of these layers and networks leads us to the concept of "Social Fabric". [Reynolds and Ali, 2008]
- Social fabrics are formed by the connectivity of individuals together which control the topology and type of interactions in the dynamic social sculpture.
- In this way, the simple interactions of individuals leads to complex community-oriented behaviors which could be expressed as an emergent phenomenon.

Social Fabric

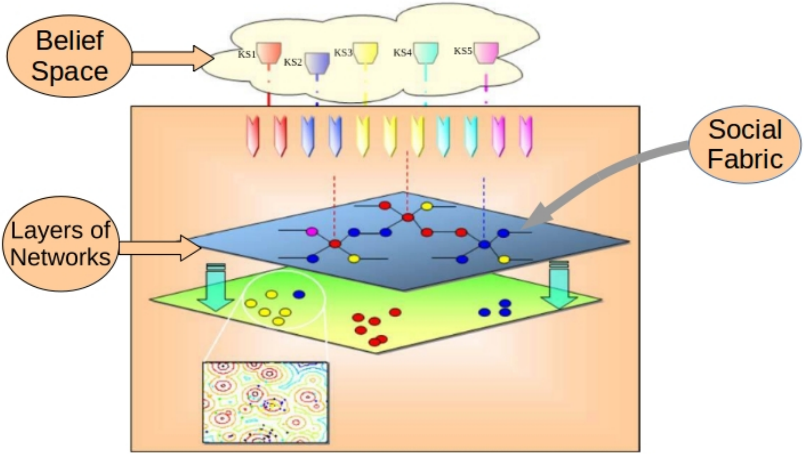


Figure: Social Fabric: [Reynolds et al., 2010]

Social Fabric

- The population is divided into multiple subgroups or tribes. [Ali et al., 2016]
- Best(elite) individuals of each tribe form the advanced layer, while the other individuals form the rudimentary layer.

- The whole search process is divided into three phases:
- Seclusion: In this stage, all the tribes work independently without any communication.
- Rapport: In this stage, the tribes start to communicate, and by selecting elite members the advanced layer is formed.
- Cohesive: Finally, all the tribes are recombined into one population, and the search process continues until meeting some stopping criteria.

Social Fabric

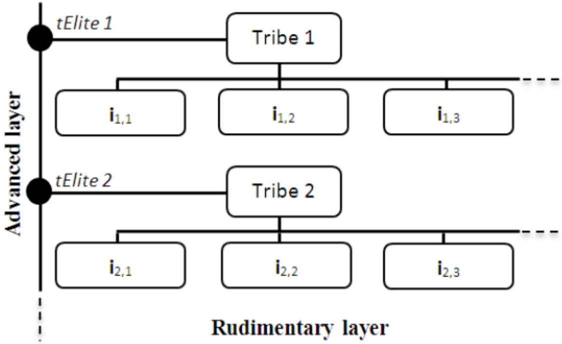


Figure: Two-layered structure of the Tribal Cultural Algorithm: [Ali et al., 2012]

Dynamic Neighborhood Restructuring

Strategic Restructuring

- Used network topologies are regular which means all the individuals have the same neighborhood size with undirected connections.
- Each tribe can change its topology in the case of stagnation.
- After a certain number of iterations without any progress in search behavior, the current topology is changed.
- The change in topology might be in either increasing the connectivity or decreasing it.

Topologies

- Ring, Tree
- Mesh, Global

Dynamic Neighborhood Restructuring

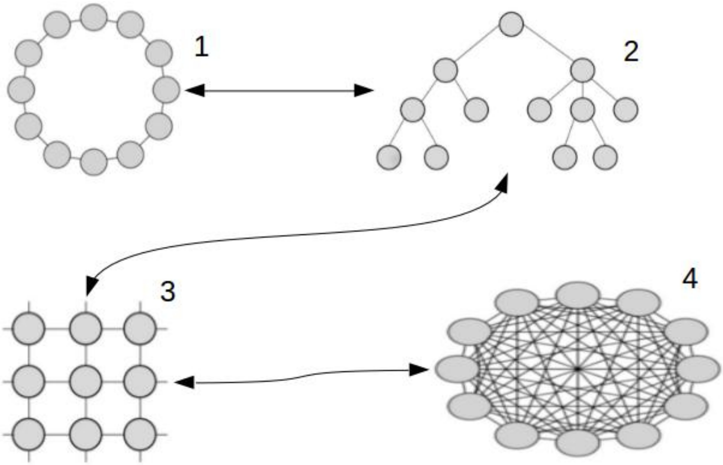


Figure: Upgrading/Downgrading Strategy

Dynamic Neighborhood Restructuring

```
if tElite == recorded_tElite then
    if stagnationCounter ≥ triggerThreshold then
        S_f ← getS_f();
        ModifyTopology(S_f);
        counterStagnation ← 0;
    else
        counterStagnation ← counterStagnation + 1;
    end
else
    stagnationCounter ← 0;
end
```

Social Fabric Infuence Function

- The social fabric represents the extent to which the influence of knowledge sources can spread through a population.
- Every individual is influenced by one of the KSs.
- Each individual receives the influencing KS of its neighbors.
- The KS that is used more than others will be chosen to influence the individual in the next iteration.

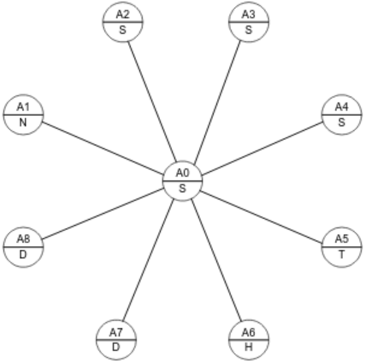


Figure: Knowledge Sources Interaction at Population Space

Social Fabric Infuence Function

- Individual *A*0 has following count of votes:
- 3 neighbors (including itself) votes for S
- 2 neighbors vote for D
- 1 neighbors votes for T
- 1 neighbors votes for N
- 1 neighbors votes for H

The Controller KS of individual A0 will be Situational for the next iteration.

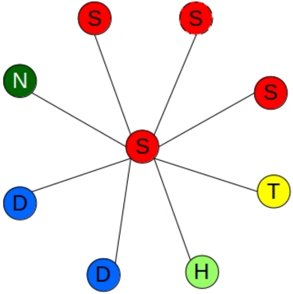
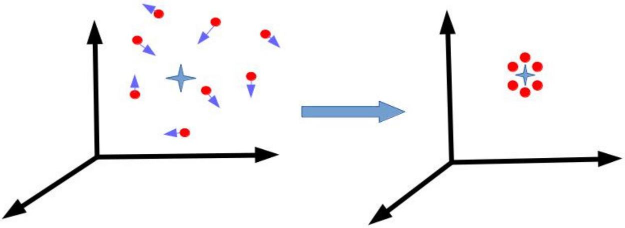


Figure: Majority Win in Belief Space

Particle Swarm Optimization

- PSO works based on the theory of social learning. Individuals (Particles) move around the search space.
- They observe other particles and adjust their velocity and direction through the search space based on their own best experience and their neighborhood best particles.
- Such behavior could be observed in natural groupings such as flocks of birds, colonies of bees, etc.



Particle Swarm Optimization

Three principles of the Collective behavior of PSO

- Evaluate: Learning cannot happen unless the individuals can evaluate the performance of themselves.
- Compare: The standards for social behaviors are set by comparison to others.
- Imitate: Particles improve their own performance through imitating of other better particles.

Particle Swarm Optimization

PSO Update Rule

The velocity V_i^d and position X_i^d of the dth dimension of the ith particle are updated as follows:

Velocity Update

$$V_i^d(t+1) = V_i^d(t) + c1 * rand1 * (pbest_i^d - X_i^d) + c2 * rand2 * (gbest^d - X_i^d)$$

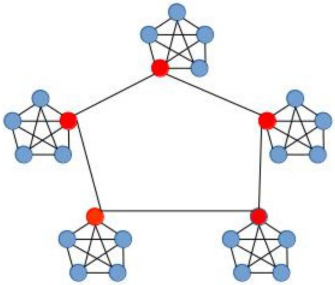
Position Update

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t)$$

Particle Swarm Optimization

Tribe-PSO

- The whole population is divided into independent tribes. [Chen et al., 2006]
- Particles fall into two layers, and the whole process consists of three phases.
- Best particles of each tribe form the upper layer of elites.



Thesis Statement

- In this research work, I am going to improve Cultural Algorithms from three aspects:
- Applying PSO algorithm to current Social Fabric based CAs.
- Introducing a Heterogenous Neighborhood Restructuring operator to increase the level of diversity.
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- For the comparison purpose, I am going to use CEC2015 benchmark optimization functions to compare my proposed approaches against already proposed algorithms.

Proposed Approach I

Heterogenous Neighborhood Restructuring

- In this type of restructuring, the topology of social fabric is not considered regular.
- It is a directed graph which means relationships between individuals are not reciprocal.
- Neighborhoods are heterogenous. Each individual has a different neighborhood size.
- In the standard Social Fabric, tribes' topologies change from a regular form into another in a macroscopic way in the presence of stagnation.
- In my proposed idea, each individual decides to increase/decrease its own neighborhood size based on its experience.

Proposed Approach I

Heterogenous Neighborhood Restructuring

- So, the Dynamic sculpture of a Social Fabric happens at the microscopic level of each individual rather than the standard's macroscopic manner.

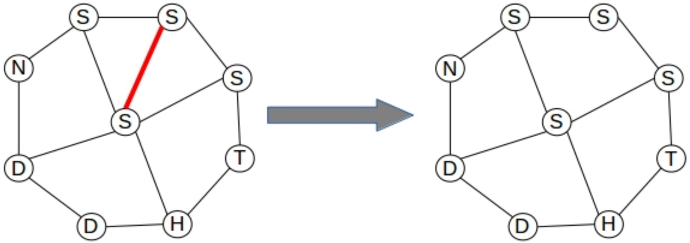

Figure:

Proposed Approach I

Pseudo-Code

if $fitness(x_i) > bestSoFar_i$ **then**
  if $stagnationCounter \geq TiggerThreshold$ **then**
    if $x_i == x_{best}$ **then**
      index = selected randomly from x_i's neighborhood
      remove x_index from x_i's neighborhood
    else
      index = selected from $\{S - x_\mathrm{i}'sneighborhood\}$
      add x_index to x_i's neighborhood
    end
    $stagnationCounter \leftarrow 0$
  else
    $stagnationCounter \leftarrow stagnationCounter + 1$
  end
else
  $stagnationCounter \leftarrow 0$

Proposed Approach II

Confidence-based Normative KS

- The standard normative KS works based on constructing a dynamic range for feasible solutions.
- The length of these ranges change based on the values of best individuals of each generation.
- Sudden changes in the values of individuals might get the normative ranges fluctuated.
- To avoid fluctuations, it needs to be improved regarding robustness.
- To do so, the concept of Confidence Interval from Statistics could be introduced here. [Papoulis and Pillai, 2002]

Proposed Approach II

Confidence-based Normative KS

- A confidence interval provides a range of values which is likely to contain a certain percentage of a population.
- There is some level of arbitrariness in choosing the range size to estimate the mean.
- Interval estimates are often desirable because the estimate of the mean varies from sample to sample.

$$(\bar{x} - q \cdot \frac{\sigma}{\sqrt{n}}, \bar{x} + q \cdot \frac{\sigma}{\sqrt{n}})$$

$\bar{x}$: mean , σ: standard deviation , q: confidence coefficient

Preliminary Results I

		SFEP	SFPSO	PSO	CAEP
T1	Mean	2.040872e+09	2.138157e+08	3.048318e+08	3.107426e+09
	Std	2.940984e+09	3.645873e+08	4.962778e+08	2.347094e+09
	Best	7.555975e+07	359556.9286	**102479.1580**	2.186939e+09
T2	Mean	3.503926e+04	1.352649e+04	2.302715e+04	7.939967e+04
	Std	2.180314e+05	6.525792e+03	8.457301e+03	2.101425e+05
	Best	1.196876e+04	**10787.6651**	13856.2910	3.782168e+04
T3	Mean	3.138285e+02	3.064714e+02	3.067392e+02	3.112132e+02
	Std	0.000000e+00	6.619418e-01	5.086404e-01	5.691358e-02
	Best	3.138285e+02	306.2688	**305.8978**	3.111638e+02
T4	Mean	3.172025e+03	1.583199e+03	1.366547e+03	2.393013e+03
	Std	0.000000e+00	1.425163e+02	2.257014e+02	0.000000e+00
	Best	3.172025e+03	1443.1549	**1038.6803**	2.393013e+03
T5	Mean	5.067958e+02	5.015503e+02	5.015435e+02	5.043716e+02
	Std	7.606342e-03	1.903829e-01	1.996635e-01	1.425465e-02
	Best	5.067913e+02	**501.2390**	501.4278	5.043702e+02

Preliminary Results II

		SFEP	SFPSO	PSO	CAEP
T6	Mean	6.034668e+02	6.009482e+02	6.017535e+02	6.066964e+02
	Std	1.013019e+00	2.992537e-01	2.406625e-01	1.518526e-06
	Best	6.023944e+02	**600.8015**	601.4588	6.066964e+02
T7	Mean	7.999019e+02	7.042910e+02	7.119572e+02	8.024372e+02
	Std	0.000000e+00	2.108978e+00	1.903651e+00	5.691358e-02
	Best	7.999019e+02	**703.7501**	709.9928	8.024372e+02
T8	Mean	5.558336e+06	8.203406e+02	8.529971e+02	5.026356e+03
	Std	0.000000e+00	1.119677e+01	5.460419e+01	1.667206e+04
	Best	5.558336e+06	816.5554	**815.2187**	8.148824e+02
T9	Mean	9.044253e+02	9.036447e+02	9.035262e+02	9.044749e+02
	Std	0.000000e+00	1.084524e-01	9.712358e-02	0.000000e+00
	Best	9.044253e+02	903.5440	**903.4610**	9.044749e+02
T10	Mean	5.004825e+05	8.964483e+04	7.352657e+04	1.662734e+07
	Std	2.716484e-01	1.987697e+05	9.838880e+04	0.000000e+00
	Best	5.004824e+05	10332.5348	**7933.8017**	1.662734e+07

Preliminary Results III

		SFEP	SFPSO	PSO	CAEP
T11	Mean	1.166344e+03	1.106949e+03	1.105856e+03	1.166454e+03
	Std	2.996447e-04	9.061842e-01	9.740308e-01	0.000000e+00
	Best	1.166344e+03	1106.3587	**1104.1271**	1.166454e+03
T12	Mean	1.509656e+03	1.300718e+03	1.282192e+03	6.295140e+03
	Std	2.199706e+02	2.087508e+01	5.158630e+01	2.864512e-02
	Best	1.393729e+03	1295.6163	**1252.4376**	6.295137e+03
T13	Mean	3.778261e+03	1.623582e+03	1.634022e+03	3.614249e+03
	Std	0.000000e+00	1.151908e+01	7.787729e+00	0.000000e+00
	Best	3.778261e+03	**1617.4672**	1626.4161	3.614249e+03
T14	Mean	1.626201e+03	1.601566e+03	1.607456e+03	1.635996e+03
	Std	0.000000e+00	1.754175e+00	7.200704e-01	0.000000e+00
	Best	1.626201e+03	**1599.4823**	1606.6267	1.635996e+03
T15	Mean	2.046239e+03	1.609993e+03	1.825546e+03	2.130541e+03
	Std	6.373723e-01	7.597716e+01	9.348504e+01	0.000000e+00
	Best	2.046175e+03	**1547.9172**	1776.2794	2.130541e+03

Figure: TimeLine

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