

# Improving Robustness in Social Fabric-based Cultural Algorithms

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**Master Thesis Defence**

# Outline

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## 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.
- 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]

$$Y = f(x_1, x_2, x_3, \dots, x_D) \quad (1)$$

For example:

$$f_1(x) = x_1^2 + 10^6 \sum_{i=2}^D x_i^2 \quad (2)$$

## Research 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 Irregular 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.

## Socially inspired algorithms

### Swarm Intelligence

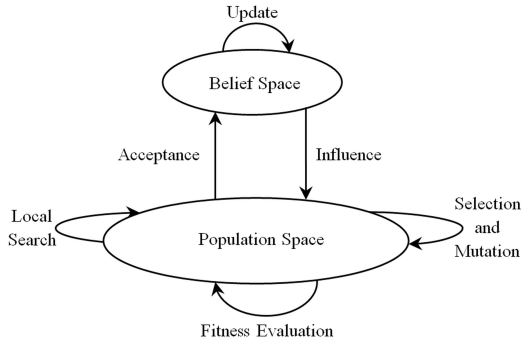
[Kennedy et al., 2001] Socially inspired algorithms(Swarm Intelligence) utilize a population of semi-rational agents(rather than dumb individuals) that have the ability to perceive their surrounding environment and cooperate with other agents in a **self-organized** manner.

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

CAs are composed of three components: **Population space**, **Belief space** and **Communication protocol**.



**Figure:** Cultural Algorithms

## Cultural Algorithms

### Belief Space

There are five types of **knowledge sources** in the Belief Space.  
[Reynolds et al., 2010]

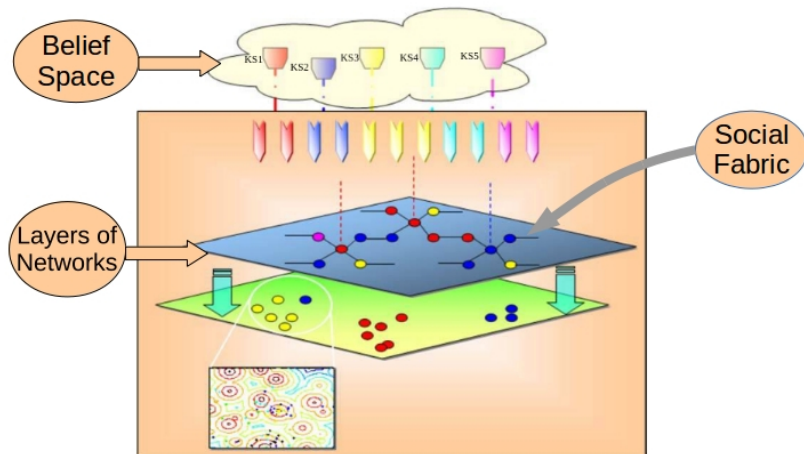
- Situational Knowledge
- Normative Knowledge
- Topographic Knowledge
- Domain Knowledge
- Historical Knowledge

## Social Fabric

### Social Fabric based CA

- In this model of CA, knowledge sources are allowed to influence the population through layers of networks.
- The interplay of these layers and networks leads us to the concept of "**Social Fabric**". [Reynolds and Ali, 2008]
- The population is divided into multiple subgroups or **tribes**. [Ali et al., 2016]

## Social Fabric



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

## Social Fabric

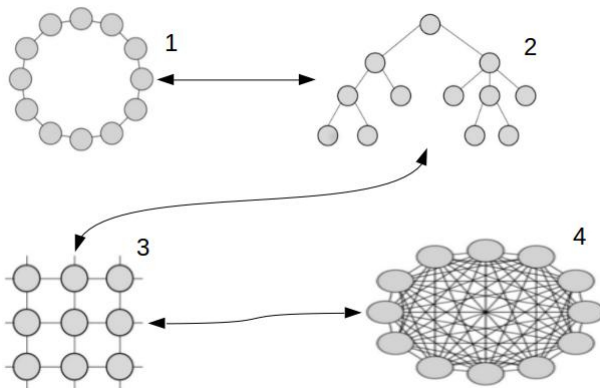


**Figure:** Three steps of evolution in Social Fabric

## Dynamic Neighborhood Restructuring

### Strategic Restructuring

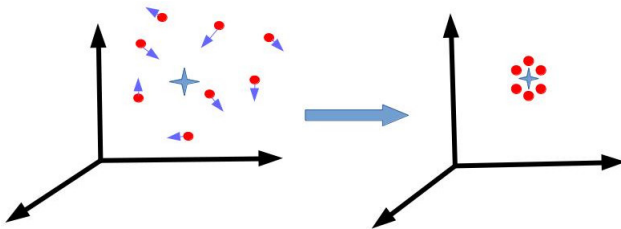
- After a certain number of iterations without any progress in search behavior, the current topology is changed.





## Particle Swarm Optimization

- PSO works based on the theory of social learning. Individuals (Particles) move around the search space.
- Such behaviours could be observed in natural groupings such as flocks of birds, colonies of bees, etc.

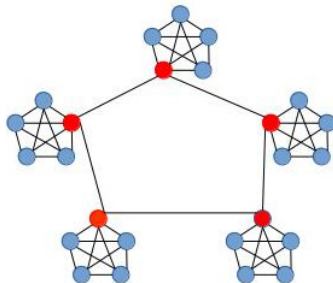


**Figure:** PSO

# 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:
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- Introducing a Irregular Neighbourhood 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

### Irregular Neighborhood Restructuring

- Each individual decides to increase/decrease its own neighbourhood size based on its experience.

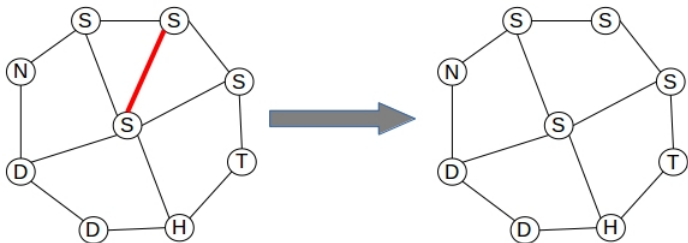


Figure:

## 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 neighbourhood
      remove  $x_{index}$  from  $x_i$ 's neighborhood
    else
      index = selected from  $\{S - x_i's neighborhood\}$ 
      add  $x_{index}$  to  $x_i$ 's neighbourhood
    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.
- A confidence interval provides a range of values which is likely to contain a certain percentage of a population.

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

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

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