Improving Robustness in Social Fabric-based Cultural Algorithms

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Master Thesis Defense

Outline

What is Evolutionary Computation(EC)?

Evolutionary Computation

Evolutionary algorithms are natural-inspired, population-based, iterational and utilize step-by-step improvement approaches. [Eiben and Smith, 2003]

- 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]

$$Y = f(x_1, x_2, x_3, \cdots, x_D) \tag{1}$$

For example:

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

Reasearch Goals

- In this research work, we improved 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, we used CEC2015 benchmark optimization functions.

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] Swarm Intelligence algorithms utilize a population of semi-rational agents that have the ability to communicate and cooperate with other agents in a self-organized manner.

- 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.

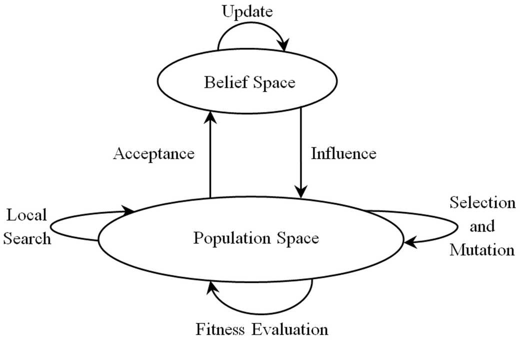


Figure: Cultural Algorithms

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

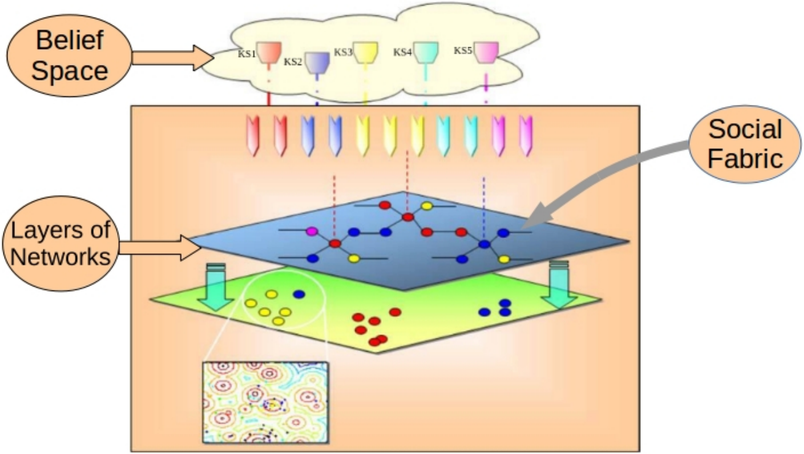
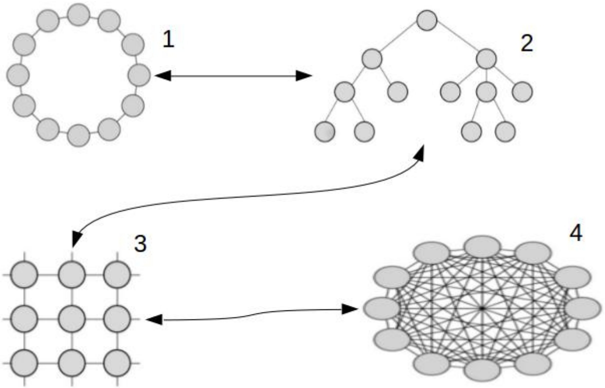


Figure: Social Fabric: [Reynolds et al., 2010]

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.

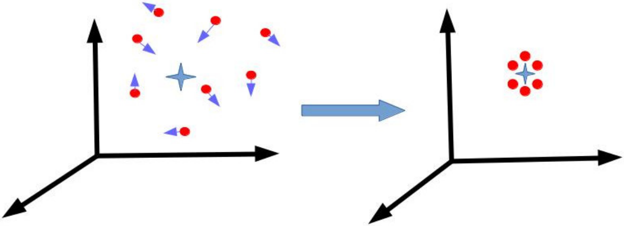
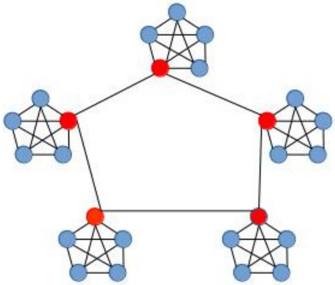


Figure: PSO

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

- Based on the No Free Lunch (NFL) theorem , there is no algorithm better than others over all cost functions.
- So, robustness is one of the most desired features in search algorithms.
- Here, robustness means to develop search strategies which adapt across different landscapes.
- We improve the robustness of CAs in both population and belief components.

Proposed Approach I

Irregular Neighborhood Restructuring

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

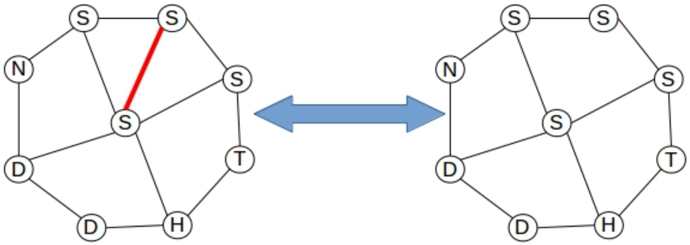


Figure:

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 $\{S - \text{x}_{\text{i}}'sneighborhood\}$
            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 , σ: standard deviation , q: confidence coefficient

Evaluation Results

Table:

		10 Dimensions				30 Dimensions			
		ISFCA	**CSFCA**	**SFCA**	**TPSO**	**ISFCA**	**CSFCA**	**SFCA**	**TPSO**
T1	**Best**	5.711750E+06	9.279149E+05	9.908642E+08	5.415067E+05	1.075684E+10	3.249525E+08	8.929425E+09	1.136511E+10
	Mean	**1.576602E+08**	4.091655E+09	9.246107E+09	2.479394E+08	**1.497176E+10**	2.168689E+10	3.786293E+10	1.718683E+10
	Std Dev	3.066335E+08	6.639431E+09	8.500530E+09	3.993037E+08	6.549615E+09	2.551255E+10	2.853221E+10	7.102879E+09
T2	**Best**	1.690419E+04	1.426333E+04	2.467511E+04	1.722714E+04	6.816396E+04	5.556673E+04	7.322705E+04	1.112664E+05
	Mean	**1.970646E+04**	2.045944E+09	3.574556E+09	2.202554E+04	**7.324758E+04**	1.090201E+08	2.266584E+09	1.324195E+05
	Std Dev	5.285568E+03	4.083561E+09	4.508859E+09	5.505069E+03	1.112414E+04	2.214664E+08	4.323029E+09	1.359207E+04
T3	**Best**	3.047026E+02	3.075572E+02	3.086619E+02	3.055813E+02	3.274619E+02	3.352212E+02	3.360418E+02	3.275333E+02
	Mean	**3.055362E+02**	3.095236E+02	3.108567E+02	3.064904E+02	**3.307785E+02**	3.400480E+02	3.410312E+02	3.305742E+02
	Std Dev	9.238688E-01	2.153735E+00	2.160320E+00	9.113892E-01	3.242337E+00	4.748334E+00	4.694844E+00	3.905358E+00
T4	**Best**	1.249122E+03	6.135802E+02	8.405862E+02	1.201363E+03	6.625647E+03	1.377132E+03	3.463489E+03	6.882440E+03
	Mean	1.401458E+03	1.392015E+03	1.725446E+03	**1.391022E+03**	6.964474E+03	**4.998230E+03**	6.375121E+03	7.270199E+03
	Std Dev	1.709634E+02	8.047924E+02	8.388958E+02	2.174364E+02	4.205720E+02	3.054933E+03	2.436783E+03	4.387157E+02
T5	**Best**	5.010726E+02	5.007002E+02	5.011836E+02	5.011289E+02	5.028153E+02	5.016618E+02	5.020560E+02	5.026209E+02
	Mean	**5.013300E+02**	5.017117E+02	5.023857E+02	5.013223E+02	5.030805E+02	5.031380E+02	5.036162E+02	**5.029678E+02**
	Std Dev	2.684750E-01	1.132619E+00	1.339239E+00	2.057213E-01	3.548877E-01	1.669277E+00	1.678840E+00	3.015601E-01
T6	**Best**	6.004334E+02	6.005685E+02	6.018524E+02	6.005062E+02	6.024192E+02	6.010681E+02	6.041570E+02	6.010077E+02
	Mean	**6.005623E+02**	6.025225E+02	6.036813E+02	6.009515E+02	6.030236E+02	6.039768E+02	6.056628E+02	**6.019309E+02**
	Std Dev	3.200289E-01	2.304279E+00	1.898523E+00	6.229300E-01	7.579661E-01	2.740738E+00	1.433152E+00	1.224478E+00
T7	**Best**	7.006188E+02	7.007965E+02	7.100632E+02	7.004902E+02	7.271223E+02	7.024000E+02	7.544377E+02	7.262179E+02
	Mean	**7.019942E+02**	7.260979E+02	7.418000E+02	7.038384E+02	**7.389013E+02**	7.605963E+02	8.116680E+02	7.498652E+02
	Std Dev	2.635216E+00	3.539268E+01	3.490056E+01	5.486938E+00	1.569694E+01	5.981939E+01	5.740507E+01	2.791729E+01

Evaluation Results

Table:

		10 Dimensions				30 Dimensions			
		ISFCA	CSFCA	SFCA	TPSO	ISFCA	CSFCA	SFCA	TPSO
T8	Best	8.060488E+02	8.475602E+02	4.118304E+03	8.057399E+02	5.240269E+04	1.095824E+03	8.508643E+04	4.126489E+05
	Mean	8.327824E+02	3.080861E+05	1.374142E+06	**8.319941E+02**	**3.363145E+05**	7.477703E+06	1.541796E+07	1.645666E+06
	Std Dev	1.428379E+02	5.970746E+05	1.940514E+06	7.254239E+01	6.891847E+05	1.270040E+07	2.340250E+07	1.667678E+06
T9	Best	9.035325E+02	9.032589E+02	9.033602E+02	9.035094E+02	9.133757E+02	9.126562E+02	9.131192E+02	9.134243E+02
	Mean	9.036469E+02	9.036343E+02	9.038043E+02	9.036178E+02	9.135258E+02	**9.133575E+02**	9.136351E+02	9.135977E+02
	Std Dev	1.008688E-01	3.372815E-01	4.187602E-01	1.037992E-01	1.312660E-01	5.882330E-01	4.913793E-01	1.390313E-01
T10	Best	2.148022E+04	2.365329E+03	6.578523E+03	1.417589E+04	6.072906E+06	2.225892E+06	8.682100E+06	1.311979E+07
	Mean	6.855882E+04	1.390710E+06	1.250589E+07	**6.576307E+04**	**1.288355E+07**	5.268560E+07	7.171894E+07	1.914266E+07
	Std Dev	7.234730E+04	1.778552E+06	2.276703E+07	7.783437E+04	7.703664E+06	5.803312E+07	5.952516E+07	8.464172E+06
T11	Best	1.104062E+03	1.106581E+03	1.105492E+03	1.104723E+03	1.153360E+03	1.155965E+03	1.290852E+03	1.134562E+03
	Mean	**1.105085E+03**	1.137076E+03	1.140188E+03	1.105442E+03	1.197912E+03	1.456495E+03	1.724513E+03	**1.174516E+03**
	Std Dev	1.339530E+00	5.229237E+01	4.994351E+01	9.340507E-01	4.334944E+01	4.589486E+02	5.277303E+02	6.235017E+01
T12	Best	1.247398E+03	1.342194E+03	1.419410E+03	1.259420E+03	2.100877E+03	1.748342E+03	2.153439E+03	2.280177E+03
	Mean	**1.284340E+03**	3.740383E+03	2.109208E+04	1.290392E+03	**2.317707E+03**	3.578488E+07	1.123866E+08	2.392247E+03
	Std Dev	4.080435E+01	4.569942E+03	3.705284E+04	4.016558E+01	2.430944E+02	7.154759E+07	1.253791E+08	1.588321E+02
T13	Best	1.622335E+03	1.635087E+03	1.676418E+03	1.618919E+03	1.723534E+03	1.740536E+03	2.380543E+03	1.732389E+03
	Mean	**1.627982E+03**	2.128914E+03	2.376883E+03	1.628781E+03	1.778258E+03	3.445463E+03	3.691270E+03	1.840829E+03
	Std Dev	7.106025E+00	6.591729E+02	7.972695E+02	1.445686E+01	9.665278E+01	2.272010E+03	1.367277E+03	1.457157E+02
T14	Best	1.601385E+03	1.591111E+03	1.597342E+03	1.604991E+03	1.646723E+03	1.660532E+03	1.693461E+03	1.658174E+03
	Mean	**1.602429E+03**	1.607129E+03	1.623200E+03	1.606235E+03	**1.676279E+03**	1.791878E+03	1.865010E+03	1.685711E+03
	Std Dev	1.577398E+00	1.953208E+01	2.617243E+01	1.478468E+00	2.842502E+01	1.553106E+02	1.760265E+02	3.566090E+01
T15	Best	1.525130E+03	1.871689E+03	1.855628E+03	1.772940E+03	2.498940E+03	2.227419E+03	3.055342E+03	2.504910E+03
	Mean	**1.589476E+03**	1.946018E+03	1.966892E+03	1.871080E+03	2.582142E+03	3.063021E+03	3.657078E+03	**2.565208E+03**
	Std Dev	8.426385E+01	8.447839E+01	1.134500E+02	7.850262E+01	9.012990E+01	1.040607E+03	1.152769E+03	8.765290E+01

Evaluation Results

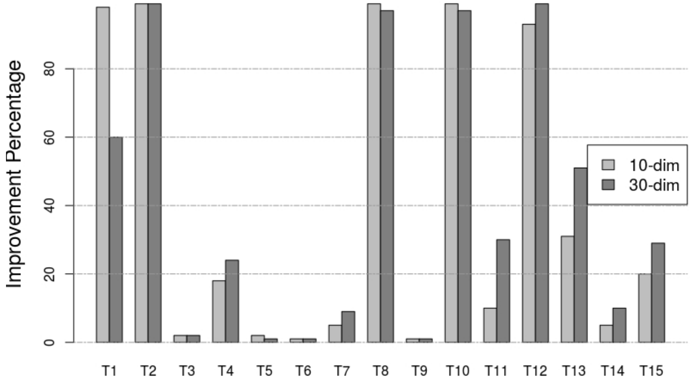


Figure: ISFCA Improvement

Evaluation Results

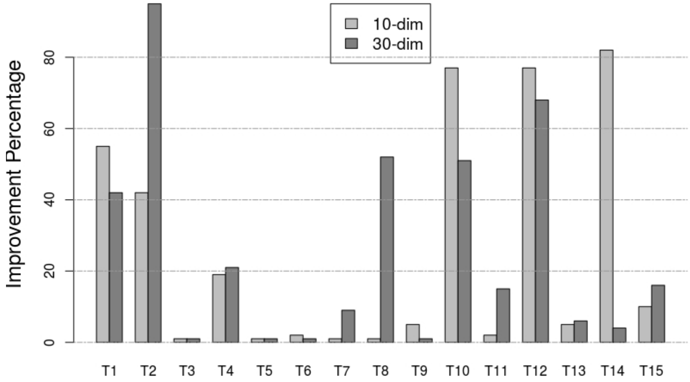


Figure: CSFCA Improvement

Application: Community Detection in Social Networks

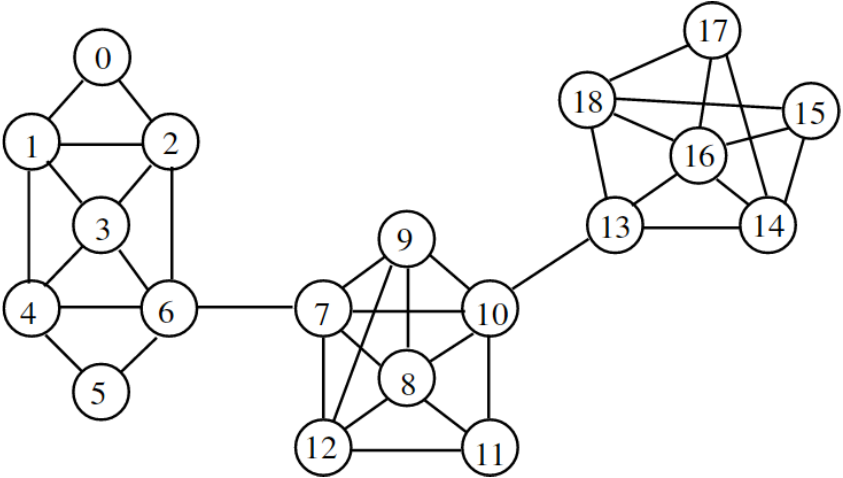


Figure: Community Detection

Application: Community Detection in Social Networks

Two factors to use EAs

- Model the individuals as solutions to the problem.
- Define a fitness function

- We adopt the Spectral method used by [Shi et al., 2009] and [Capocci et al., 2005]
- The spectral method weighted distance defines a dissimilarity measure between network nodes.

$$dis_{i,j} = \sqrt{\sum_{k=1}^{m-1} A_k * (v_{ki} - v_{kj})} \tag{3}$$

Application: Community Detection in Social Networks

Center existence array				Center array			
$flag_1$	$flag_2$	...	$flag_m$	$center_1$	$center_2$	...	$center_m$

Figure: Structure of Particles

Modularity-based Fitness Function

$$Q = \sum_{i=1}^{n} (e_{ii} - a_i^2) \quad (4)$$

$$a_i = \sum_{j=1}^{n} e_{ij} \quad (5)$$

Publications

- Title: Improving Robustness in Social Fabric-based Cultural Algorithms with Two New Approaches in Population and Belief Spaces
- Conference: FLAIRS-2017
- Status: Accepted for publication

- Title: Self-Organized Neighborhood Restructuring in Social Fabric
- Confenece: Canadian AI 2017
- Status: Submitted.

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