

Swarm Intelligence

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Introduction

- Swarm Intelligence. Nature inspired algorithms to solve:
 - Combinatorial domain optimization problems (ACO, MTPSO, RFD...)
 - Continuous domain optimization problems (PSO, ABC, DE...)
- Many (partially) independent entities cooperating to find a solution.
- Individuals are relatively homogeneous and interact with simple rules
- Balance:
 - Exploration of the overall search space
 - Exploitation of the most promising areas



Introduction

- There are many (many, many, many) swarm intelligence metaheuristics.
- EvolutionaryComputationBestiary https://github.com/fcampelo/EC-Bestiary



- Let's try to focus on the mathematical basis of classical metaheuristics
- Most of the original metaheuristics only provide a new analogy, but are

essentially the same as other more classical metaheuristics



Swarm Intelligence: Overall view

- Comprehensive Taxonomies of Nature- and Bio-inspired Optimization: Inspiration versus Algorithmic Behavior, Critical Analysis and Recommendations Clasification by behavior:
 - Differential vector movement (207/323 => 64.09%).
 - All population (13/323 => 4.02%). FA, CDA, ...
 - Groups based (25/323 => 7.75%). CSO, BA, ...
 - Representative based (169/323 => **52.32%**). **PSO**, ABC, ...
 - Solution creation (116/323 => 35.91%):
 - Combination (108/323 => 33.43%). GA, Cuckoo Search,...
 - Stigmergy (8/323 => 2.48%). ACO, RFD,...

- Inspired on social behavior of a colony of bird flocks
- Minimize fitness function $f: \mathbb{R}^n \rightarrow \mathbb{R}$
- Each particle has an initial random position and an initial random v vector
- In each iteration: $\mathbf{v}_{i,d} \leftarrow \omega \ \mathbf{v}_{i,d} + \phi_p \ r_p \ (\mathbf{p}_{i,d} \mathbf{x}_{i,d}) + \phi_g \ r_g \ (\mathbf{g}_d \mathbf{x}_{i,d})$
 - Inertia
 - Vector towards best local position p_{i,d} found by itself
 - Vector towards best global position g_d found by the swarm



- In each iteration:
 - $\mathbf{v}_{i,d} \leftarrow \omega \mathbf{v}_{i,d} + \phi_p r_p (\mathbf{p}_{i,d} \mathbf{x}_{i,d}) + \phi_g r_g (\mathbf{g}_d \mathbf{x}_{i,d})$
 - \bullet $\mathbf{x}_{i} \leftarrow \mathbf{x}_{i} + \mathbf{v}_{i}$
 - if $f(\mathbf{x}_i) < f(\mathbf{p}_i)$ then Update the particle's best known position: $\mathbf{p}_i \leftarrow \mathbf{x}_i$
 - if $f(\mathbf{p}_i) < f(\mathbf{g})$ then Update the swarm's best known position: $\mathbf{g} \leftarrow \mathbf{p}_i$
 - \bullet r_p and r_g are random numbers between 0 and 1
 - \bullet ϕ_p ϕ_g are parameters of the metaheuristic. (inertia, cognitive component, and social component)



- Initialization:
 - Randomly distributed or around candidate solution
 - Velocity vectors randomly distributed or zero
- Implementation details:
 - Keep positions (and velocity) inside search space
 - Closest position inside search space
 - Velocity zero or inverse (whip back)



- Parameter tunning:
 - Classical values: social and cognitive around 2.
 - Pedersen values:

https://www.researchgate.net/profile/Mohamed-Mourad-Lafifi/post/Which-is-the-best-swarm-size-in-

PSO/attachment/5b5b6f85b53d2f89289c14e1/AS%3A653084896288769%40153271898 1208/download/Good+Parameters+for+Particle+Swarm+Optimization.pdf

https://eprints.soton.ac.uk/71755/



- Variations
 - Neighborhood (ring, adaptive topologies, etc.)
 - Mutations, hybrid methods, simplifications, discrete version, etc.
 - Multiobjective versions



- Your next task:
 - Develop your own PSO program
 - Check it with classical benchmark functions (Sphere, Rastringin,
 - Rosenbrock, etc.) Evolutionary programming made faster
 - Compare results with different parameters. Apply statistical tests:
 - https://www.isa.us.es/3.0/tool/statservice/
 - http://tec.citius.usc.es/stac/ranking.html
 - https://www.statskingdom.com/kruskal-wallis-calculator.html