Adaptive Spatial System Emergence from Community Swarm Optimization

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Outline

1. Swarm Intelligence: scientific and historical context
2. Swarm Intelligence, Complexity and Emergence
3. Swarm Intelligence relevance for applications
4. A Community based approach
5. Conclusion
Swarm Intelligence: scientific and historical context

Hardware history and computing concept impact

- Sequential architecture
  - sequential programming
- Parallel architecture
  - Splitting problem into predefined sub-problems
  - Master and Slaves model: centralized decomposition
- Distributed architecture
  - Decentralized approach based on processes interaction
Swarm Intelligence: scientific and historical context

Software history and problem solving concept impact

- Sequential programming and procedural programming
- Object-oriented programming
  - Operational entities
  - Private or public data and methods
  - Interfacing by public methods
  - Program consists in the objects interaction
- Agent-based programming
  - Autonomous entities within an environment
  - Include life cycle and eventually complex behavior
  - Interfacing by perceptions and actions
  - Program consists in virtual world simulation
Modelling history and simulating concept impact

- Numerical analysis computing
  - Equational approach: describes the global system behavior
  - Law-based description
  - Program consists in trajectories computing
  - Top-down approach

- Complex systems and distributed computing
  - Conceptual approach where entities are described by behavior
  - Rule-based description
  - Program consists in virtual world simulation
  - The global system behavior emerges from the entities interaction
  - Bottom-up approach
1. Swarm Intelligence: scientific and historical context
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Swarm Intelligence is based on distributed solvers

- Not planned sequential solvers
- Not splitting the problem into many smaller ones and assembling the sub-solutions
- But distributed solvers
  - which do not describe themselves the solution
  - but where the solution emerges from their interactions
Emergence

- *weak* emergence: from a set of interacting entities, we can observe a system formation with some specific properties not described inside the entities themselves.
- *strong* emergence: the emergent system feed-back on its own entities and can control them.
Swarm Intelligence, Complexity and Emergence

Some swarm intelligence methods

- **Ant Colony optimization**: virtual ants moving on a graph which represents the contextual environment;
- **Particle swarm optimization**: virtual particles collectively moving on a solution space;
- **Community swarm optimization**: virtual automata population evolving and moving on spatial environment.
Adaptive Spatial System Emergence

SI-Context
SI-Complexity
Applications
CSO
Conclusion

Graph support
ACO

Pheromone deposit

Best positions from local and environmental memorization
Solution space support
PSO

Co-evolution of Spatial/Behavior properties
By fitness computation
Geo-physical support
CSO

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## Outline

1. Swarm Intelligence: scientific and historical context
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Swarm Intelligence relevance for applications

Optimization! ... and what else?

- When the optimization function could not be defined because the system and its properties are emerging
- The problem is not described by optimization but by adaptation
Geographical and social systems

- Urban dynamics
  - Gentrification: self-organization dynamic of city centers attraction and impact on the urban structure which will redefine its own centers by feed-back processes.
  - Mobility network: how the 3-D urban morphology emerge from the mobility interaction network and how these emergent morphologies feed-back on the interaction network?
Swarm Intelligence relevance for applications

Geographical and social systems

- Land-use modelling (Territorial intelligence)
  - Regional European Union help: What is the impact in respect of the interaction network (economical, environmental, ...) inside and outside the target region to be helped.

- Sustainable development
  - Complex network of objectives: economical, social and environmental
  - Multi-scale in space and time, according to each objective
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Community Definition

**Definition**: A *community* is a system or an organization which is characterized by a *spatial* property, a *behavior* property and the interaction between the both.

**Examples**:
- Community in Ecology (food chains);
- Schelling’s segregation model patterns are the results of such emergent communities, based on elementary behaviors.
Community swarm optimization

**Principles**

- Entities describing rule-based transitions systems (agent behaviors) and implemented by automata with multiplicities ...
- ... on which we can defined behavioral distance allowing emergence of organizations
- Implementation of the system feed-back (adaptation or control) using genetic processes ...
- ... and leading to emergent communities, mixing spatial and behavioral properties.
Spatial Behavioral Automata

Automata-based Agent Behavior

Agent

Goal

Behaviour

perceptions

actions
Automata with multiplicities

Agent behavior is modelled by automata with multiplicities which is defined by

- A set of perception represented by an alphabet
- A set of actions represented by a semi-ring $K$
- A set of states with a subset of initial states and a subset of final states
- A set of transitions between states which is generate by a perception in input and which generate an action in output
Automata with multiplicities

Because the set of actions $K$ is a **semi-ring**, we can represented the automata using a linear representation (vectors and matrices), we can defined many kinds of operators on these automata and so improve automatic processes on agent management.
Spatial Behavioral Automata: example

- Strategy modeling using *probabilistic* automata for game theory
- Automata based model for player behavior with adversary:
  - 2 behavioral states: Cooperate (s1: C) or Defect (s2: D)
  - Probabilistic transition from one state to another according to what made the adversary at the previous step


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![Diagram of spatial behavioral automata](image)
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\[
\begin{array}{c}
C_1 \\
\rightarrow \\
\Downarrow C:0.7 \\
D_2
\end{array}
\]

**LINEAR REPRESENTATION**

<table>
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<th>1</th>
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<tr>
<td>M(C)</td>
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Input vector:

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<tbody>
<tr>
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<td>0.7</td>
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Probabilistic transition matrix:

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<td>M(D)</td>
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Output vector:

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Adaptive Spatial System Emergence
21/31
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![Diagram of a spatial behavioral automata model](image)

**Linear Representation**

- **Input Vector**
  - \( \begin{bmatrix} 1 \\ 2 \end{bmatrix} \)
  - Options: \( \begin{bmatrix} 0.3 \\ 0.7 \end{bmatrix} \)

- **Output Vector**
  - \( \begin{bmatrix} 1 \\ 2 \end{bmatrix} \)
  - \( \begin{bmatrix} 1 \\ 2 \end{bmatrix} \)

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![Diagram of Behavioral Automata]

**Linear Representation**

<table>
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<tbody>
<tr>
<td>1</td>
<td></td>
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<td>0.7</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>0.6</td>
<td>0.4</td>
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- Input vector
- Output vector

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![Diagram of Behavioral Automata](image)

**LINEAR REPRESENTATION**

<table>
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<th>1</th>
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<td>0.3</td>
<td>0.7</td>
<td>0.1</td>
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</tr>
<tr>
<td>0.8</td>
<td>0.2</td>
<td>0.6</td>
<td>0.4</td>
</tr>
</tbody>
</table>

**Input vector:** [0.8, 0.2]

**Output vector:** [0.3, 0.7]

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Spatial automata and associated distances

- A spatial agent is defined by
  - Spatial coordinates
  - A behavior modeled by an automaton with multiplicities

- A **spatial distance** between 2 agents, can be computed according to their spatial coordinates

- A **behavioral distance** between 2 agents can be computed by the distance between the vectors which stores all the coefficients of the linear representation of the agent behavior automata.
Spatial Behavioral Genetic Automata

Genetic operators on automata population

- Genetic operators deal with **population of individuals** as spatial behavioral automata.
- **Individual** is described by a **chromosome** which is a sequence of **alleles** (elementary information).
- Here, the chromosomes are coding the transition matrices of the behavioral automata linear representation.
- Here, an allele is a matrix line ...
Genetic operators on automata population

... and the chromosome is the set of the matrix lines of all the transition matrices
Community Swarm Optimization Algorithm

Overview

- CSO Algorithm consists in generating an initial virtual automata population describing some spatial transition rules system;
- This virtual automata population evolves and moves on a spatial environment;
- The evolution (and the moving) follows a genetic algorithm including a selection process associated to a fitness function.
We can define the fitness of each agent as following:

- We compute his neighbourhood, using the *spatial distance*.
- We sum the *behavioral distance* of the agent itself with all the others agents included in the neighbourhood.
- We define the fitness as the inverse of the average of the previous sum.

Self-organization communities emerge from the use of this fitness inside a genetic algorithm.
Community Swarm Optimization Algorithm

Community Detection associated to fitness function

Let $\mathcal{V}_x$ a neighbourhood of the agent $x$, relatively to its spatial location. We define $f(x)$ the agent fitness of the agent $x$ as:

$$f(x) = \begin{cases} \frac{\text{card}(\mathcal{V}_x)}{\sum_{y_i \in \mathcal{V}_x} d(x, y_i)^2} & \text{if } \sum_{y_i \in \mathcal{V}_x} d(x, y_i)^2 \neq 0 \\ \infty & \text{otherwise} \end{cases}$$

where $d(x, y)$ is the behavioral semi-distance between the two agents $x$ and $y$. 
CSO Algorithm: example ... following
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CSO specificity

- With the comparison of other methods from this category (ACO and PSO), CSO differs mainly on the modelling purpose;
- CSO deals with transition rules included data structures (automata) and algebraic operators allowing to implement automatic computation for self-organization.
CSO Applications

Presented here as a generic method, CSO is efficient in engineering problems where spatial characteristics are not only additional coordinates for the data but contribute to self-organization.

Urban and land usage management need this kind of modelling to improve decision making.