Adaptive Spatial System Emergence from Community Swarm Optimization

Rawan Ghnemat\textsuperscript{(1)},
Cyrille Bertelle\textsuperscript{(1)} & Gérard H.E. Duchamp\textsuperscript{(2)}

(1) LITIS - Le Havre University - France
(2) LIPN - Paris XIII University - France

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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
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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.
Co-evolution of Spatial/Behavior properties
By fitness computation

Geo-physical support
CSO

Best positions from local and enviromental memorization
Solution space support
PSO

Graph support
ACO

Pheromon deposit

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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.
Swarm Intelligence relevance for applications

**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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A Community based approach

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

Environment

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Spatial Behavioral Automata

**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
Spatial Behavioral Automata

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 makes the adversary at the previous step
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![Diagram of Spatial Behavioral Automata](image-url)

**Linear Representation**

**Input Vector**

- C1
- D2

**Output Vector**

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**LINEAR REPRESENTATION**

![Diagram of behavioral automata]

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**Linear Representation**

- Input vector: [1, 2]
- Output vector: [1, 2]
- Transition matrix:
  - M(C): 
    - 1: 0.3
    - 2: 0.7
  - M(D): 
    - 2: 1

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![Diagram of Automata]

**Linear Representation**

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
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<tbody>
<tr>
<td>1</td>
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<td>0.7</td>
</tr>
<tr>
<td>2</td>
<td>0.6</td>
<td>0.4</td>
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**Input Vector**

**Output Vector**

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![Diagram](image)

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<tbody>
<tr>
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</tr>
<tr>
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<td>0.2</td>
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Input vector: [0.8, 0.2]

Output vector:

```
<table>
<thead>
<tr>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
<td>0.7</td>
</tr>
</tbody>
</table>
```

M(C) = 0.3, M(D) = 0.7

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Spatial Behavioral Automata

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.
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.
Community Swarm Optimization Algorithm

Community Detection associated to fitness function

- We can defined 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.

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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 $y$. 

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CSO Algorithm: example ... following
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Conclusion and Perspectives

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.