Distributed Intelligent Systems – W13: Self-Aggregation and Self-Assembly in Natural and Artificial Systems
Outline

• Self-aggregation in artificial systems
• Collective decisions mediated by self-aggregation (mixed societies)
• Self-assembly
  – General background
  – Examples
Self-Aggregation in Artificial Systems
Robot Self-Aggregation using Wireless Communication - Overview

[Correll & Martinoli, *IJRR* 2011]

- Eg. 2 clusters of 3 robots, 6 of 1 robot
- Webots experiments using Alice II with radio, 12 robots total
- Arena diameter: 1 m
- Communication range: 7-12 cm
- Simplified com model

Real robotic node: Alice II with 802.15.4 com module
Original Inspiration: Aggregation in Gregarious Arthropods

- Aggregation in Cockroaches
- Individual Behavior is well studied
- Probability to rest is a function of the number of cockroaches nearby
- Probability to move decreases when in larger aggregates

© Sempo, Halloy, Detrain & Deneubourg
Individual Behavioral Parameters

Data collected by Jeanson et al. *(Animal Behavior 2004)*
Experimental Setup

- Submicroscopic model (Webots)
- Estimate of neighborhood using local communication used as an “omnidirectional teammate sensor”
- Local communication:
  - presence or absence of a teammate in the communication range
  - use of static or from a large set dynamically randomly chosen IDs for facilitation of the discrimination
  - no additional explicit information shared (e.g., counting process involving multi-hop, etc.)
- Objective: relation between individual and collective dynamics rather than biological accuracy
- Systematic experiments (thousands of runs) infeasible with biological agents
Individual Robot Behavior

Note: avoidance behavior for walls implemented but neither represented here nor captured by the models (impact negligible)
Microscopic and Macroscopic Modeling
Assumptions

• A robot moves through the environment (random walk) during which it encounters other robots with *constant* probability

• The probability to encounter one robot is $p_c$, the probability to encounter and join a cluster of $n$ robots $p_{join}(n)$; the probability of leaving such cluster $p_{leave}(n)$

➢ **Uniform distribution** of objects in the environment and **linear super-position** of encountering probabilities
Probabilistic Finite State Machine for an Individual Robot

\[ p_c = \text{probability per time step to encounter another robot} \]
\[ N_x = \text{fraction of time spent in state } x \]
“Passive” State Transitions

Example: 4 robots change their state without actually moving
Probabilistic Finite State Machine for the Whole System

\[ N_s = \text{average number of robots in search} \]
\[ N_j = \text{average number of robots in an aggregate of size } j \]
Probabilistic Finite State Machine

Searching robot joins cluster of size $j-1$

$C_{j-1}, N_{j-1}$

One robot resumes search

$C_j, N_j = C_j$

$C_{j+1}, N_{j+1}$

Searching robot joins cluster of size $j$

One robot resumes search
Number of Agents in a j-size Cluster

- Flows from a single aggregate

\[ j p^\text{join}(j) \]
\[ j p^\text{leave}(j) \]

\[ j p^\text{join}(j-1) \]
\[ j p^\text{leave}(j+1) \]
Average Number of Agents in a \( j \)-size Cluster

\[
N_j(k) = N_j(k)j_p c p_{\text{join}}(j) + N_s(k)N_{j-1}(k)j_p c p_{\text{join}}(j-1) - N_{j+1}(k)j_p \text{leave}(j+1) - N_j(k)j_p \text{leave}(j)
\]

\[
N_{j+1}(k)j_p \text{leave}(j+1)
\]

\[
16
\]
Sample Results and Discussion
Temporal Evolution of the Self-Aggregation Process (12 robots)

Submicroscopic model (Webots)
- 1500 runs
- 3 h (10800 s) per run
- sample time 10 s
- 10 cm communication range

Macroscopic model
Modulating the Encountering Probability by the Communication Range (12 robots)

- 7cm communication range
- 1500 runs

- 12 cm communication range
- 1500 runs
Discussion

• The “encountering probability” is indeed a function of the communication range, which leads to a bifurcation of the system dynamics (scattered vs. giant component)

• Aggregation performance of the biological algorithm very low

• Might be the sole choice for micro-robots
Discussion

• Modeling limitations:
  – Clusters are assumed to be circular
  – Only one individual joins/leaves at a time
  – Clusters do not split/merge

• Function of robot shape/sensorial characteristics
Self-Aggregation in Mixed Natural-Artificial Systems
The LEURRE Project

- **Leurre**: European project focusing on mixed insect-robot societies ([http://leurre.ulb.ac.be](http://leurre.ulb.ac.be))

- Relevant *Leurre* partners for the presented work:
  - ULB (coordinator, modeling, experimental work with insects/robots)
  - Uni Rennes/CNRS (chemistry)
  - EPFL – ASL/LSRO (mobile robots design and development)
  - EPFL – DISAL (vision-based tracking and modelling)
Collectively Selecting a Shelter

**Goal of the project:** quantitatively characterize the self-organized collective decision-making process of a cockroach society by unravelling and influencing the local interaction rules

- A simple decision-making scenario: 1 arena, 2 shelters
- Shelters of the same and different darkness
- Groups of pure cockroaches (16), mixed robot+cockroaches (12+4)
- Infiltration using chemical camouflage and statistical behavioral model

[Halloy et al., *Science*, 2007]
Sample Results

Legend: mixed, pure; shelter 1, shelter 2

A. Symmetric shelters (infiltration)  
B. Asymmetric shelters (active control)
Self-Assembly in Natural and Artificial Systems
What is Self-Assembly?

Spontaneous organization of pre-existing units into spatial structures or patterns without external guidance.

Self-Assembly at All Scales

29 orders of magnitude, same underlying mechanism!

Carbon nanotube, about $10^{-8}$ m

Our galaxy, the Milky Way, about $10^{21}$ m
### What is NOT Self-Assembly?

<table>
<thead>
<tr>
<th>Planned and externally guided constructions</th>
<th>Unstructured aggregates</th>
<th>Living beings, because they are not made of pre-existing units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gazprom building, St-Petersburg, $10^2$ m</td>
<td>Boxelder bug aggregate, $10^{-3}$ m</td>
<td>Various animals</td>
</tr>
</tbody>
</table>

Sequential, limited scalability (from a few millimeters up to a few kilometers)

Aggregation may serve a purpose (e.g., protection, collective decision-making), but the structure itself does not.

Self-assembly may have played a key role in the initial appearance of life.
Self-Assembly at All Scales

A. Crystal structure of a ribosome [Yusupov et al., 2001]
B. Scaffolded DNA origami of 100 nm in diameter [Rothemund, Caltech]
C. Capillary SA of 10-μm-sized hexagonal plates into large crystal structures [Whitesides, Harvard]
D. SA of 1-mm-sized hexagonal plates using “capillary bond” [Whitesides, Harvard]
E. SA of electrical networks [Whitesides, Harvard]
F. Electromechanical programmable parts specifically designed for SA [Klavins, University of Washington]
G. A swarm of mobile robots capable of SA [Dorigo, Université Libre de Bruxelles]
Ingredients and Features

- Ingredients of Self-Assembly:
  1. **Positive feedback**: binding force, structural reinforcement
  2. **Negative feedback**: repulsive force (otherwise, merely aggregation)
  3. **Multiple reversible interactions**
  4. **Randomness**

- Features of Self-Assembly:
  - **Robustness**: self-assembly deals with component defects, environmental noise and external perturbations
  - **Parallelism**: self-assembly occurs wherever there are interacting components
  - **Scalability**: self-assembly is a strategy applicable at all scales, and even across scales
  - **Ubiquity**: structures form spontaneously at all scales in Nature, and most of them exhibit similarities across scales
Self-Assembly of Micro-Systems
A Motivation for Studying Self-Assembly

Manufacturing and coordination of ultra-small distributed intelligent systems:

Left: A microrobot (10 μm) is inoculating a red blood cell against some kind of disease. Right: This nanoscaled device (1 nm) enables a nanorobot to catch HIV individuals and destroy them.
The quest for miniaturization

How to go from the Alice robot (2cm in size)…

...to fully-fledged microrobots?
Limitations of the Top-Down Approach

HOW TO ASSEMBLE

THESE

INTO THESE

USING THESE?

ANSWER: LET THEM ASSEMBLE THEMSELVES!
Self-Assembly of Micro-Systems

**Self-Assembly**

- Hydrophobic interaction and capillary forces (in fluid)
- Van der Waals forces (in dry state)
- Experimental challenges: imaging (3D, high speed camera, microscope) and controllability
Intelligent… and less intelligent agents

Alice mobile robot
- Typical size: 2 centimeters
- Typical swarm size: < 100 units
- Sensing, computation, communication (only local)
- Controllable self-locomoted units (but quite noisy)

MEMS
- Typical size: 50 to 500 μm
- Typical swarm size: > 10^4 units
- No sensing, computation or communication, but local interactions only
- Stochastic motion only
Multi-Level Modeling Methodology

Macroscopic 1: rate equations, mean field approach, whole population

Macroscopic 2: Chemical Reaction Network, stochastic simulations

Microscopic 1: Monte Carlo model, 1 robot = 1 agent, non-spatial

Microscopic 2: Agent-Based model, 1 robot = 1 agent, spatial

Realistic: faithful representation of the robots (e.g., geometry, S&A) and the environment (e.g., friction, gravity, inertia)

Physical reality: real experiments, imaging with overhead cameras, tracking software
Multi-Level Modeling

- **Macro-deterministic**: rate equations, mean field approach, whole population
- **Macro-stochastic**: Chemical Reaction Network, stochastic simulations
- **Microscopic (non-spatial)**: Monte Carlo model, 1 molecule = 1 agent
- **Microscopic (spatial)**: Agent-Based model, 1 molecule = 1 agent

Underlying physical platforms and submicroscopic models may vary dramatically.
10 runs
452 species
1474 reactions

Self-Assembly of Passive Lilies

- 40 runs
- 6 species
- 12 reactions

Self-Assembly of Passive Lilies

- [Di Mario et al., IROS 2011]
- [Mermoud, PhD EPFL 2012]

40

1.96·σ

Aggregates of size 2

Population

Aggregates of size 2

mean

1.96·σ

Aggregates of size 3

Aggregates of size 4

Population

Population

Time [s]

[Di Mario et al., IROS 2011] 40
Automated Model-Based Design

[Mermod et al., ICRA 2012]
Model-Based Control of Self-Assembly

- Case study with four **real passive Lilies**
- Two modes of agitation (bang-bang):
  1. High agitation (exploration)
  2. Low agitation (exploitation)
- Simultaneous modeling & optimization approach
- Completely automated and real-time

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<tr>
<th>Assemblies</th>
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<tr>
<td>A</td>
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**Target**
Qualitative Results

Real-Time Model-Based Control of Stochastic Self-Assembly

Gregory Mermoud, Massimo Mastrangeli, Utkarsh Upadhyay and Alcherio Martinoli
Quantitative results

40 runs of 30 minutes using 4 real passive Lilies
Guided, Programmable Self-Assembly of cm-scale Robots: The Kilobot Project
The Kilobot Project - Hardware

- 1024 robots
- About 3 cm in diameter

The Kilobot Project - Software

The Kilobot Project – The Self-Assembly Algorithm

The Kilobot in Action

Self-Organizing Systems Research Group

Harvard University
School of Engineering and Applied Sciences
Wyss Institute for Biologically Inspired Engineering
The Kilobot Project – An Example

Self-Organizing Systems Research Group

Harvard University
School of Engineering and Applied Sciences
Wyss Institute for Biologically Inspired Engineering
Discussion

• Provably correct algorithm

• Elements of centralization:
  – Seed robots define the coordinate system
  – Targeted shape encoded via programming in each robot
  – Gradient building starting from seed robots

• Limited parallelism: movement on the outer edge of the shape of specific elements

• Decentralized components:
  – Relative localization
  – Randomly initialized edge following
Conclusion
Take Home Messages

• Self-aggregation can be modeled with the usual multi-level modeling techniques; the resulting models at the macroscopic level are very similar to those of object aggregation

• Self-aggregation can facilitate collective decisions, especially in systems endowed with low-range communication

• Self-assembly implies the constitution of structures and ordered spatial pattern (rather than just aggregate) and constituting elements that incorporate all the required assembly mechanisms (although they are not necessarily endowed with self-locomotion capabilities)

• Self-assembly can happen at all scales and is a powerful, parallel, potentially cheap coordination principle for a number of manufacturing applications in which traditional techniques cannot be used or have an excessive cost

• Self-assembly can be guided and can exploit centralized templates
Additional Literature – Week 13

Papers


Course Conclusion
Take Home Messages

• Distributed Intelligent Systems (DISs) show natural and artificial (virtual or real) forms

• Artificial and natural DISs differ quite a bit in their physical substrate and algorithms/design solutions proposed for natural systems can often be applied in a straightforward way in virtual scenarios but with more care in the real world

• Various classes of algorithms, model-based and data-driven (machine-learning) methods have been presented in the course for the coordination, analysis and synthesis of DISs
Take Home Messages

- Local interaction mechanisms ensure system scalability; individual simplicity often implies additional robustness at the cost of a reduced efficiency.
- Self-organization is a key, scalable coordination mechanism based on local interactions.
- Self-assembly is a form of self-organization focusing on spatial patterns.
- Swarm Intelligence is one form of distributed intelligence relying on self-organization as coordination mechanism; it often also leverages stigmergy as indirect communication mechanism; it targets systems consisting of a large number of simple units.
Take Home Messages

• Further local capabilities (e.g., additional computation resources, explicit communication, and localization) can be used to enhance the collective performance

• Further coordination mechanisms exploiting longer range, explicit communication, and points of centralization can be competitive at the cost of a higher node complexity or reduced mobility

• Volume/mass/cost of single nodes determine available energy, S&A accuracy, communication, computation, and mobility capabilities, etc. and software/hardware choices must be well matched to obtain competitive systems
The end: Thanks for your attention over the whole course!