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

• Self-aggregation in artificial systems
• Collective decision mediated by self-aggregation (mixed societies)
• Self-assembly
  – General background
  – Artificial examples (sub-mm and cm scales)
Self-Aggregation in Artificial Systems
Robot Self-Aggregation using Wireless Communication - Overview

- 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 Zigbee-compliant com module

[Correll & Martinoli, *IJRR* 2011]
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.)
• 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)
Probabilistic Modeling of Individual Dynamics
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 a cluster of $n$ robots $np_c$.
- **Uniform distribution** of objects in the environment and **linear super-position** of encountering probabilities.
Probabilistic Finite State Machine

\[ np_c \ p_{\text{join}}(n) \]

Search

\[ np_c \ p_{\text{leave}}(n) \]

n-Cluster

\[ p_c = \text{probability per time step to encounter another robot} \]
Probabilistic Finite State Machine

Robots joining/leaving aggregates

"Passive" state transitions

\[ N_s = \text{number of robots in search} \]
\[ N_j = \text{number of robots in an aggregate of size } j \]
“Passive” State Transitions

Example: 4 robots change their state without actually moving
Probabilistic Modeling of
Collective Dynamics
Probabilistic Finite State Machine
Number of Agents in a j-size Cluster

- Flows from a *single* aggregate

\[ j_{pc} p_{join}(j) \]

\[ j_{pc} p_{join}(j-1) \]

\[ j_{pc} p_{join}(j+1) \]
Average Number of Agents in a $j$-size Cluster

\[
N_s(k) N_j(k) p_\text{join}(j) \quad N_s(k) N_{j-1}(k) j p_\text{join}(j-1)
\]

\[
N_j(k) p_\text{leave}(j) \quad N_{j+1}(k) j p_\text{leave}(j+1)
\]

\[
N_j(k+1) = N_j(k) + p_c N_s(k) j [p_\text{join}(j-1) N_{j-1}(k) - p_\text{join}(j) N_j(k)] - p_\text{leave}(j) N_j(k) j + p_\text{leave}(j+1) N_{j+1}(k) j
\]
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
Temporal evolution of the Self-Aggregation Process (1 run)
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*, Nov. 2007]
Sample Results

Legend: mixed, pure; shelter 1, shelter 2

A. Symmetric shelters (infiltration)  
B. Asymmetric shelters (active control)

Experiment

Macroscopic Model
The EPFL Tool Contributions

1. Robots as a flexible, interactive, societal “microscope”

   [Asadpour et al., *ARS J.*, 2006]

2. A marker-less vision-based tracking tool: SwisTrack

   [Correll et al., IROS 2006, Lochmatter et al., IROS 2008]; http://sourceforge.net/projects/swistrack

3. Multi-level modeling

   $N_j(k+1) = N_j(k) p_{j,N}(k) \left[ p_{s,N}(j-1) N_{s,j}(k) - p_{j,N}(j) N_j(k) \right] - p_{s,s}(j) N_j(k) j + p_{s,s}(j+1) N_{s,j}(k) j$

   Macroscopic model

   Agent-based microscopic model

   Module-based microscopic model

   Target system

   [Correll et al., *ALife J.*, in prep.]
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?

Planned and externally guided constructions

Living beings, because they are not made of pre-existing units

Unstructured aggregates

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

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.

Gazprom building, St-Petersburg, $10^2$ m

Boxelder bug aggregate, $10^{-3}$ m

Various animals
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, UniversitéLibre 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
Motivation for Studying Self-Assembly (1)

Scientific understanding of a broad variety of phenomena:

- Water ripples: $\sim 10^{-3}$ m
- Seashell: $\sim 10^{-2}$ m
- School of fish: $\sim 10^1$ m
- DNA origami: $\sim 10^{-7}$ m
- Tornado: $\sim 10^2$ m
- Cyclone: $\sim 10^6$ m
Motivation for Studying Self-Assembly (2)

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 (2 cm 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-locomotored 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
  - $X_a + X_d \rightarrow X_2$
  - $X_a + X_d \rightarrow X_{i+1}$

- **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 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

Underlying physical reality (and, therefore submicroscopic models) may vary dramatically!
Ex. 1: Self-Assembly of Alice Robots

Goal
- Formation of chains
- Physical testbed for models at multiple abstraction levels

Self-assembly
- "soft" binding force
  (implemented through local IR communication)

Advantages
- Controllable, but still miniaturized
- Experimental ease: imaging, controllability, flexibility

[Evans et al., ICRA 2010]
Single Robot Algorithm

Deterministic vs. stochastic variant
Deterministic Controller

Bonded Alices communicate with each other to determine the length of their chain

\[ \text{msg} = 4 \]
\[ \text{msg} = \text{msg} + 1 \]
\[ \text{msg} = 2 \]
\[ \text{msg} = 4 \]
Deterministic Controller - Sample Results with 19 robots

Submicroscopic (Webots)  Macroscopic (stochastic CRN)
Every second, an Alice leaves its current bond depending on some probability.
Stochastic Controller - Sample Results with 19 robots

Submicroscopic (Webots)  Macroscopic (stochastic CRN)
Ex. 2: Self-Assembly Micro-Systems

- **Ground truth:** spatial microscopic model - implemented in Netlogo
- **Abstraction:** shape of the building blocks, most physical effects (e.g., friction, fluid dynamics)
- **Assumption:** building blocks can be represented as simple agents with a certain orientation and a single preferential direction
- **Discretization** of alignment state
- **Random motion** is described by a Langevin equation (Brownian motion):
  \[
  m \ddot{v} = -\gamma v + \mathcal{N}(0, \eta \nu_r^2)
  \]
  - friction term
  - agitation term
- **Collisions** handled in a deterministic fashion.

[Mermoud et al., AAMAS 2009]
Microscopic Non-Spatial Model

- **Abstraction**: spatiality, i.e. the position and orientation of each agent
- **Assumption**: the system is well-mixed, homogeneous and isotropic
- This Monte Carlo model does not capture spatiality, but still keeps track of each aggregation/disaggregation event in the system.
- Geometric approximation for encountering probability (volume swept):
  \[ p_c \sim \frac{v_r T w_d}{A_{tot}} \]

- Energy-based formulation of the break-up probabilities, which depend on the alignment of the building blocks:
  \[ p_b(s_i) = \exp \left( \frac{\Delta E(s_i)}{\alpha \nu^2_s} \right) \]
Macroscopic Model

- **Abstraction**: the state (i.e., whether it is in an aggregate or not, and with which agent) of each individual agent
- **Assumption**: the system can be modeled using a mean field approach based on rate equations.
- Our model is based on **difference equations** that keep track of the number of individuals in each state.
- Capturing alignment by discretizing of the space of pairs into $K$ different alignment states, each with a different **break-up probability**:
Excellent agreement between non-spatial models (red and blue). Spatial model (agent-based, in green) converges slower: lower mixing.
Mean field approximation validity

Also, the faithfulness of macroscopic model with respect to microscopic spatial model degrades as the total number of building blocks $N_0$ decreases.
Optimizing Self-Assembly

- Agitation brings mobility to the building blocks, but also mitigates the stability of bonds: find the appropriate tradeoff!
- Non-linearity, exploration vs exploitation tradeoff: self-assembly is a difficult control problem!
- Optimization of control and design parameters requires accurate and computationally inexpensive models.
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.
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 model-based and data-driven (machine-learning) methods have been presented in the course for analysis and synthesis of DISs

• Formal methods for DISs are still in their infancy
Take Home Messages

• Local interaction mechanisms insure system scalability; individual simplicity often implies additional robustness at the cost of a reduced efficiency

• Self-organization is one of the key, scalable coordination mechanisms based on local interactions

• Definition of self-organization in natural systems is well-established, in artificial systems (exploiting massive amount of discrete information) is an open question

• Swarm Intelligence is one form of distributed intelligence relying on self-organization
Take Home Messages

• Stigmergy, environmental templates and further local capabilities (e.g., intelligence, explicit communication, 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

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