Swarm Intelligence - W2: Course Overview and Foraging Strategies in Ant Societies
Course Syllabus and Summary
Goal

- Course overview
- Short description of each chapter so that course projects can be better chosen (topic list distributed on Nov 3, response with lab+hwk set 1, definitive assignment Nov 17)
- 7 main blocks over 13 weeks
- A few slides per block
Syllabus Rationale

- **Idea I**: for each specific chapter, showing biological and artificial counterpart, both at computational and embedded system level
- **Idea II**: move from multi-agent algorithms gradually to real hardware, in particular: multi-agent algorithms $\rightarrow$ multi-agent embodied simulators $\rightarrow$ real sensor networks $\rightarrow$ real multi-robot systems $\rightarrow$ real collective hybrid systems (static and self-locomoted nodes)
Trail Laying/Following
Biological Mechanisms and Models

Choice occurs randomly

\[ L = 14 \text{ cm} \]

(Deneubourg et al., 1990)

% of ant passages on the two branches

Time (minutes)

Branch A

Branch B

(Deneubourg et al., 1990)
From Ant Networks to ACO

- **ACO = Ant Colony Optimization**
- Ants can solve difficult network problems (minimal spanning tree, coping with edge interruptions, etc.)
- Trail laying/following mechanism can be transported to virtual ants

Results for a triangular network (3 nest super-colony) with *Linepithema humile* (Argentine ants) [Aron, Deneubourg, Goss, Pasteels, 1991]
The Travel Salesman Problem

Graph $(N,E)$

- $N$: set of cities (nodes)
- $E$: set of connecting roads (links)
- $d_{ij}$: distance between city $i$ and $j$

**Problem:** Find the shortest path which allow the salesman to visit once and only once each city in the graph

**Difficulty:** NP-hard problem; time for computing the shortest route grows in a nonpolynomial way with the number of cities in the network -> metaheuristics provide near-optimal solutions!
Application of Trail/Laying Mechanisms

Communication Networks

Routing table of node k (N-nodes net)

<table>
<thead>
<tr>
<th>Destination node</th>
<th>1</th>
<th>...</th>
<th>j</th>
<th>...</th>
<th>k-1</th>
<th>k+1</th>
<th>...</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Next node</td>
<td>(i_1)</td>
<td>...</td>
<td>(i_j)</td>
<td>...</td>
<td>(i_{k-1})</td>
<td>(i_{k+1})</td>
<td>...</td>
<td>(i_N)</td>
</tr>
</tbody>
</table>

Ex. Routing problem
(\text{Di Caro \\& Dorigo, 1998})

Swarm Robotics

Ex. Virtual Pheromones
(Payton et al., 2001)
Collective Movements
Reynolds’ Rules for Flocking

1. **Separation**: avoid collisions with nearby flockmates

2. **Alignment**: attempt to match velocity (speed and direction) with nearby flockmates

3. **Cohesion**: attempt to stay close to nearby flockmates

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**Position control**

**Velocity control**

**Position control**

separation

alignment

cohesion
Implementation of Flocking Rules in Artificial Embedded Agents

Real robots

Moorebot Flocking (3x)

Realistic simulator (Webots)
Particle Swarm Optimization (PSO)
Modeling and Learning in Collective Embedded Systems
Multi-Level Modeling Methodology

\[ \frac{dN_n(t)}{dt} = \sum_{n'} W(n | n', t) N'_{n'}(t) - \sum_{n'} W(n' | n, t) N_n(t) \]

Rate equations, mean field approach, whole swarm

- Multi-agent models, robot details abstracted, only relevant feature captured, 1 agent = 1 robot
- Intra-robot (e.g., S&A) and environment (e.g., physics) details reproduced faithfully
- Info on controller, S&A, morphology and environmental features
A Case Study: Stick-Pulling

Physical Set-Up

- 2-6 robots
- 4 sticks
- 40 cm radius arena

Collaboration via indirect communication

- IR reflective band
- Proximity sensors
- Arm elevation sensor
Full Macroscopic Model

For instance, for the average number of robots in searching mode:

\[ N_s(k+1) = N_s(k) - [\Delta g_1(k) + \Delta g_2(k) + p_w + p_R] N_s(k) + \Delta g_1(k-T_{cga})\Gamma(k;T_a)N_s(k-T_{cga}) + \Delta g_2(k-T_{ca})N_s(k-T_{ca}) + \Delta g_2(k-T_{cda})N_s(k-T_{cda}) + p_w N_s(k-T_a) + p_R N_s(k-T_{ia}) \]

with time-varying coefficients (nonlinear coupling):

\[ \Delta g_1(k) = p_{g1}[M_0 - N_g(k) - N_d(k)] \]
\[ \Delta g_2(k) = p_{g2} N_g(k) \]
\[ \Gamma(k;T_{SL}) = \prod_{j=k-T_{SL}}^{k} [1 - p_{g2} N_s(j)] \]

- 6 states: 5 DE + 1 cons. EQ
- \( T_i, T_a, T_d, T_c \neq 0; T_{xyz} = T_x + T_y + T_z \)
- \( T_{SL} = \) Shift Left duration
- [Martinoli et al., *IJRR*, 2004]
Machine-Learning Methods for Control Design an Optimization

- Evaluative: multi-agent (GA, PSO) or single-agent (RL)
- Mainly off-line but also a few light version for on-line learning

Specific issue for collective embedded systems:
- credit assignment problem
- increased noise resistance
- implementation on a distributed platform

Ex. GA (100 agents) and 2 robots
Division of Labor
The control of task allocation explained with a fixed-threshold model

The lower the threshold, the lower can be the stimulus for achieving a given response; respectively, the lower the threshold, the higher will be the response of an individual for a given stimulus.
The Division of Labor and the Flexibility of Social Roles

The control of task allocation explained with a variable-threshold model

The lower the threshold, the lower can be the stimulus for achieving a given response; respectively, the lower the threshold, the higher will be the response of an individual for a given stimulus.
Market-Based Coordination

Robots simulate a market economy:

- Tasks, resources are commodities of measurable worth.

- When robot performs task:
  - gets paid for service it provided (+ $)
  - pays for resources it consumed (- $)

- Robots trade tasks and resources to maximize profit

**Idea!** pursuit of individual profit leads to efficient team solutions.

- Robust, fast, handle complex tasks
- Can take advantage of centralized planning
Hands on Real Distributed Platforms
Khepera I and II

- For course project only
- Availability: immediate
- Several additional tools available (gripper, 1-D vision, radio)
- Precise odometry
- Preferred operational mode: single robot + cable (rotating contact)
- Total 10 robots
E-Puck Robot

- For course project and labs
- Availability: from January
- Multi-robot operation ok
- No gripper, poor odometry
- Total 100 robots

- DsPIC30F6014 platform up to 30Mips
- 2 motors
- 8 IR sensors
- 3 microphones
- Color camera
- 3 axis accelerometer
- Bluetooth serial transmission
- A light ring around the robot
- Bus connectors to allow board stack
- Area to add a floor sensor board
- Robot size is Ø 7cm x 5cm
E-Puck Communication Module

- ZigBee ready platform
- TinyOS on MSP430 microcontroller
- ~10cm to ~100m transmission range via software and hardware signal attenuation
- I²C communication with E-Puck
- Programmable through E-Puck Bluetooth serial transmission
- Resetable via I²C commands
MICAz

- Atmel ATmega128L
  - 8 bit microprocessor, ~8MHz
  - 128kB program memory, 4kB SRAM
  - 512kB external flash (data logger)
- Chipcon CC2420
  - 802.15.4 (Zigbee)
- 2 AA batteries
  - about 5 days active (15-20 mA)
  - about 20 years sleeping (15-20 µA)
- TinyOS
Hybrid Networks

Real world

Realistic simulations

On a DESKTOP!!!!
Assembling & Disassembling
Corpse Aggregation in the Ant

*Messor Sancta*

Reduction of the spread of infection? Chretien (1996)
Lumer and Faieta’s Algorithm (1994)

Attribute Space Projection and Discretization:

1. The attribute space is projected on a smaller dimension space (e.g. 1, 2). **Assumption:** the projection space has to be chosen so that the distances intra-clusters are smaller than distances inter-cluster

2. The projected space is discretized (it can be seen as a sub-space of $\mathbb{Z}^2$) in order to achieve computational efficiency. Discretization is problem-specific. Clusterizing and sorting agents operate on this grid space.
Aggregation/segregation using (and of) Robots

Becker et al, 1994

Holland & Melhuish, 1998
Qualitative Stigmergy

Features

• Successive stimuli are qualitatively different. This process generates a self-assembly dynamics.

Note: Here insects transport bricks that self-assemble; in other systems the elements are active and can self-assemble themselves
Research Topics in Embedded Swarm Intelligence
A Case Study: Odor Source Localization

• Given an enclosed area containing an odor plume, find the source of the odor plume as efficiently as possible

• Applications:
  – Hazardous waste cleanup
  – Plume leakages identification
  – Humanitarian demining

• Task Decomposition
  – Plume finding
  – Plume traversal
  – Source declaration
Distributed Plume Tracing

• Single robot behavior

• Crude multi-robot collaboration
  – adapted to binary odor detection (hit/no hit)
  – signaling (directional broadcast)
  – attraction/repulsion signals
Coverage of Regular Structures

- Case study: turbine inspection
- Goal: complete sensor coverage of the turbine/compressor blades
- Technical challenges limit possible designs of robotic sensors
- Test-bed: 40 Alice II
- Could pave the way for similar applications in coverage/inspection of engineered or natural, regular structures with heavily constrains on robotic equipment
Foraging Strategies in Ant Societies
Outline

• Foraging Strategies
  – Individual search
  – Recruitment-based mechanisms

• Bridges experiments in the lab
  – Experimental results
  – Microscopic models and Montecarlo simulations

• The role of inaccuracies of chemical communication
Different Foraging Strategies in Ants
Not All Foraging Strategies are Collective and based on Stigmergy …

- Example: *Cataglyphis* desert ant
- Excellent study by Prof. R. Wehner (University of Zuerich, Emeritus)
- Individual foraging strategy
- Underlying mechanisms
  - Internal compass (polarization of sun light)
  - Dead-reckoning (path integration on neural chains for leg control)
  - Local search (around 1-2 m from the nest)
- Extremely accurate navigation: averaged error of a few tens of cm over 500 m path!
More individual Foraging Strategies

Individual navigation + learning capabilities for memorizing the foraging zone
Tandem Recruitment Strategies

- Mediated by thropallaxis, antennal contact
- Based on food chemical signatures on the ant body
Les différentes stratégies de récolte chez les fourmis

3. Recrutement de groupe

Recrutement de groupe chez la fourmi Camponotus socius

Leader
Mass Recruitment Strategies

Les différentes stratégies de récolte chez les fourmis

4. Recrutement de masse

Recrutement de masse chez la fourmi Solenopsis geminata
Collective Hunting Strategies

Les différentes stratégies de récolte chez les fourmis

Chasse de groupe

Raids de chasse chez les fourmis légionnaires (Eciton burchelli)
Mass Recruitment
Formation of Recruitment Trails in Ants

Note: more quantitative models of foraging in open space next week
Number of Ants at the Food Source vs. Time

Le recrutement de masse

1. Caractéristiques du recrutement

Croissance logistique (Pierre François Verhulst, 1845) du nombre de fourmis présentes à la source de nourriture

Growing phase (positive feedback)

Saturation phase (negative feedback)
Behavior of Individual Ants

Sequence of actions performed by an ant communicating the discovery of a food source

- Food source
- Foraging area
- Nest

1. **Picking up food**
2. **Laying a chemical trail**
3. **Stimulating nest mates**
4. **Following the trail**
5. **Deposition of food**
Trail Laying Mechanisms

Physiology

- Trail is laid by the active deposition of pheromone from a gland at the tip of the ant’s intestine
- The ant can vary the frequency of deposit and probably also the amount of deposit

Pheromones

- May be one of several
- Evaporates
- Diffuses
- Pheromone deposits on trail sum
- Some lab measurements suggest half-life of 45 min
- But can persist for months
Trail Following Mechanisms

- Pheromone sensed via antennae
- General strategy: turn towards the side with the strongest stimulation (osmotropotaxis)
- Can acquire a trail by encountering it: strength of trail and angle of encounter are important
- Often move faster on stronger trails
- Some ants may be able to sense the direction in which a trail was laid...
Stochastic Individual Behavior Combined with the Amplification of Information can lead to Collective Decisions
How does individual behavior with a strong stochastic component lead to statistically predictable behavior at the level of the colony and collective decisions?
(from Week 1)
Basic Ingredients of Self-Organization

• Multiple interactions
• Randomness
• Positive feedback
  – E.g., recruitment and reinforcement
• Negative feedback
  – E.g., limited number of available foragers
Experimental Studies

• Most of the quantitative studies have been carried out in the lab because:
  – Controlled environmental conditions
  – Repeated runs for statistics

• Studies in the field might be influenced by:
  – Multiple food sources
  – Predators and competitors
  – Environmental changes (temperature, climate, etc.)
Exploration: The Inaccuracy of Chemical Communication
Termite Following a Pheromone Trace

Prof. J.-L. Deneubourg (ULB, Bruxelles)
Ants can Reacquire a Trail by Local Search

Rôle du hasard et du bruit dans l'organisation de la récolte

1. Orientation des fourmis le long d'une piste

Osmotropotaxie (Hangartner, 1967)
Probability of Trail Losing depends on the Ant Species

Example: Accuracy of recruitment of the first recruit (Verhaeghe et al., 1980)

<table>
<thead>
<tr>
<th>Successful recruitments (%)</th>
<th>Tetramorium impurum</th>
<th>Tapinoma erraticum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of trail followed (%)</td>
<td>18</td>
<td>74</td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>68</td>
</tr>
</tbody>
</table>

*Tapinoma* follow trails much more reliably than *Tetramorium* → depends on the environment the species have evolved (food scattering, etc.)
Probability of Trail Losing is Constant over Time

- The longer the traveled path and the smaller is the number of ants on the trail
- Appears to be independent of phenomena such as learning or sensory adaptive response (at least under such short time scale)

Log \# of ants on the trail as a function of the traveled path for a constant pheromone concentration
Probability of Trail Losing depends on Chemical Concentration

The higher is the pheromone concentration and the more reliably can be followed a trail

Mean path length as a function of the pheromone concentration
Biological Significance of the Exploitation-Exploration Balance

Does the accuracy of the chemical communication channel used by ants increase or decrease their efficiency?

• Noise can have a certain flexible value for the organization of the society.

• The fact that a significant proportion of recruits get lost en route can be of benefit when food is scattered throughout the environment or when several sources are present simultaneously.

• If too many ants get lost for a given food scattering the efficiency of recruitment also decreases.

Sacrifice a little bit efficiency in order to be robust at facing environmental unpredictability.
Bridge Experiments: Selecting the Shortest Path
The Suspended, Symmetric Bridge Experiment

Food source

Two branches (A and B) of the same length connect nest and food source

Nest

© J.-L. Deneubourg
Experimental Results

![Graph showing the percentage of ant passages on two branches over time]

- **Branch A**
- **Branch B**

% of ant passages on the two branches vs. Time (minutes)
Microscopic Model
(Deneubourg 1990)

\[ P_A = \frac{(k + A_i)^n}{(k + A_i)^n + (k + B_i)^n} = 1 - P_B \]

Probabilistic choice of an agent at the bridge’s bifurcation points

\[ P_A \text{ and } P_B \text{ : probability for the ant } i+1 \text{ to pick up the branch A or B respectively} \]
\[ A_i \text{ : number of ants having chosen branch A} \]
\[ B_i \text{ : number of ants having chosen branch B} \]
\[ n \text{ (model parameter): degree of nonlinearity} \]
\[ k \text{ (model parameter): degree of attraction of a unmarked branch} \]

\[ A_{i+1} = \begin{cases} A_i + 1 & \text{if } \delta \leq P_A \\ A_i & \text{if } \delta > P_A \end{cases} \]

\[ B_{i+1} = \begin{cases} B_i + 1 & \text{if } \delta > P_A \\ B_i & \text{if } \delta \leq P_A \end{cases} \]

\[ A_i + B_i = i \]

\[ \delta = \text{uniform random variable on } [0,1] \]
Parameters of the Choice Function

- The higher is n and the faster is the selection of one of the branches (sharper curve); n high corresponds to high exploitation
- The greater k, the higher the attractiveness of a unmarked branch and therefore the higher is the probability of agents of making random choices (i.e. not based on pheromones concentration deposited by other ants); k high corresponds to high exploration
Model vs. Experiments

Total number of ants having traversed the bridge

% of ant passages on the dominant branch

Parameters that fit experimental data:
- $n = 2$
- $k = 20$

Note: microscopic model -> Montecarlo simulations
The Suspended, Asymmetric Bridge Experiment

**Food source**

- Two branches (A and B) differing in their length (length ratio $r$) connect nest and food source
- Test for the optimization capabilities of ants

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All Bridge Experiments

4 different experimental scenarios

1. $r = 1$  
   $l = 14 \text{ cm}$

2. $r = 1.4$  
   $L = 20 \text{ cm}$

3. $r = 2$  
   $L = 28 \text{ cm}$

4. $r = 2$  
   $L = 28 \text{ cm}$

Shortest branch added later
Selection of the Shortest Branch

Repeated experiments with different ant colonies of the same ant species (*Linepithema Humile*).
What happens if the shorter branch is presented after 30 minutes?

• Argentine Ants (*Linepithema Humile*) get stuck on the longer branch (mainly pheromone-based navigation), see previous slide.

• *Lasius Niger* ants find the shorter branch because they integrate other navigation modalities (compass, dead-reckoning) with pheromone navigation -> U-Turns (different from random walk)!

• *Pharaoh ants* recognize the right way to go from geometry of trails (trails geometry provide polarity information!), again dead-reckoning/compass capabilities!
The previous model does not work any more: distance/traveling time has to be considered in order to incorporate the geometry of the bridge.

Multi-agent simulation incorporating pheromone deposition, avoidance rules, … point simulator (take into account trajectories but no body) by Prof. M. Dorigo (ULB Bruxelles).
Additional Literature – Week 2

Books

Papers