Self-organized Multi-robot Task Allocation

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October 2010

Outline

Multi-robot Task Allocation (MRTA)

What is MRTA?

In a multi-tasking environment dynamically allocate appropriate tasks to appropriate robots considering the changes in task-requirements, team-performance and environment.

Why MRTA is difficult?

In typical large distributed multi-robot teams:

- No centralized planner or coordinator
- Robots have limited ability
  $\longrightarrow$ to sense, communicate and interact locally
- Robots have limited world-views
  $\longrightarrow$ knowledge of past, present and future actions of others

Major Approaches for MRTA

Explicit allocation

Through explicit modelling of environment, tasks, robot capabilities. Some forms are: knowledge based, market based, role/value based, control theoretic.

- Pros: Straight-forward to design, implement and analyse formally.
- Cons: Not suitable for large teams (> 10) and heavy dependency on explicit global broadcast communication.

Self-organized allocation

Through emergent group behaviour produced by the local interaction and implicit or local communication. Most common form is: response threshold based approach.

- Pros: Suitable for large teams, no explicit model, implicit/local communication
- Cons: Difficult to design, implement, analyse and limited to one specific global task.

Self-organization

What is Self-organization?

Pattern formation in both biological and physical systems through the interactions internal to the system (Camazine et al. 2001).

Why Self-organized approach to MRTA?

- Implementing simple agent behaviours is economical
  $\longrightarrow$ no sophisticated cognitive agents.
- Easily scalable for large robot-teams and tasks
  $\longrightarrow$ no explicit modelling of environment.
- Fault-tolerant
  $\longrightarrow$ no leaders, templates or blue-prints.
- Energy-efficient
  $\longrightarrow$ no costly communication or computation overhead.

Ingredients of Self-organization

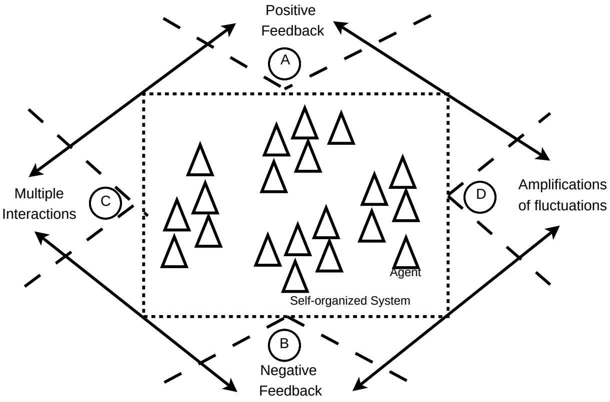

Figure: The four ingredients of self-organization

Examples:

A	Ants' recruitments to food source through trail laying/following
B	Overcrowding at food sources
C	Various types of communications through peer-to-peer, broadcast or stigmergic
D	Randomness and/or error in trail-following that leads to discover new food sources

Self-regulation of an Agent

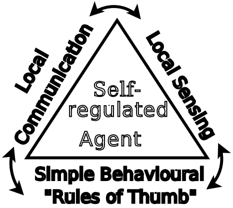

Figure: Three major interfaces of a self-organized agent

Self-organization in birds nesting

Simple behavioural rules	Follow: *"I nest close where you nest ... unless overcrowded"*
Local communication	Communications through local broad-cast signals
Local interactions	Courtship display with neighbours

Requirements of AFM

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Properties of Agents & System under AFM

AFM and Self-organization

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Issues related to using AFM in real-world application

Centralized and Local Communication Models

- Software code on *HEAD*

Hybrid-event Driven Architecture on D-Bus

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Results: Shop-floor Work-load and Active Workers

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Results: Task-performance, Task-specialization and Energy-usage

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Results: Task-specialization

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Results: Energy-usage

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Results: Communication Loads

Conclusions

- AFM solves the MRTA issue for a relatively large group
  $\longrightarrow$ under both centralized and local communication strategies.
- Task-performance varies under different strategies
  $\longrightarrow$ for small group, task-performance degrades in centralized communication
  $\longrightarrow$ for large group, local communication increases task-specialization and significantly reduces motions.
- AFM can model complex multi-tasking environment
  $\longrightarrow$ such as a dynamic manufacturing shop-floor.
- Maximizing information flow is not useful
  $\longrightarrow$ under a stochastic task-allocation process, more information tends to cause more task-switching behaviours.

General Contributions

- Self-organization in artificial systems
  $\longrightarrow$ Self-organized allocation produces specialized workers even when the group size is *small* ($<$ 10).
- Role of communication in self-organization
  $\longrightarrow$ Local communication in task-allocation outperforms centralized one in terms of group level task-specialization and energy usage.
- Large-scale system development
  $\longrightarrow$ Bottom-up de-coupled construction of *large* artificial system yields higher advantages particularly, flexibility and integration with inter-operable elements.

Specific Contributions

- Interpreted AFM
  $\longrightarrow$ as a basic mechanism for multi-robot task-allocation
- Validated the effectiveness of AFM
  $\longrightarrow$ with reasonably *large* number of real robots
- Compared the performances of two communication and sensing strategies:
  1. Centralized communication like **Polistes** wasps
  2. Local communication like **Polybia** wasps
- Developed a *flexible* multi-robot control architecture
  $\longrightarrow$ using **D-Bus** inter-process communication
- Classified MRTA solutions focusing three major issues:
  1. Organization of task-allocation
  2. Communication and
  3. Interaction

Future works

- Deploying our task-allocation model in various task settings
  $\longrightarrow$ e.g. dynamic tasks, co-operative tasks, heterogeneous tasks.
- Find optimum communication range
  $\longrightarrow$ as a property of self-regulation of individuals.
- Real-world implementation
  $\longrightarrow$ e.g. warehouse automation, manufacturing shop-floor or any other multi-tasking environment.