Self-organized Multi-robot Task Allocation

Md Omar Faruque Sarker

Cognitive Robotics Research Centre
University of Wales, Newport

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

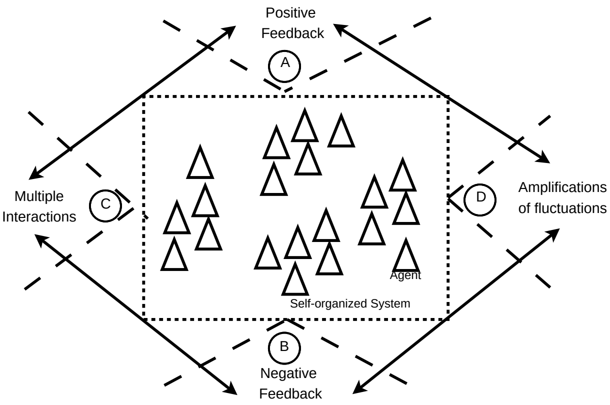


Figure: The four ingredients of self-organization

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

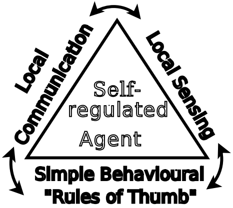


Figure: Three major interfaces of a self-organized agent

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

Attractive Field Model (AFM)

Features of AFM

- Interdisciplinary: From the observation of ant, human and robotic social systems.
- Abstraction: Sufficient abstraction to accommodate different sensing and communication models.

Requirements of AFM

1. Concurrence: The simultaneous presence of several options or tasks, at least a single task and the option of not doing any task.
2. Continuous flow of information: Establish a flow of information to perceive tasks and receive feedback on system performance.
3. Sensitization: Each individual must have different levels of preference or *sensitivity* to the available tasks.
4. Forgetting: A mechanism by which the sensitisation levels are reduced or *forgotten* e.g. a slow general decay of sensitisation.

AFM as a Bipartite Network

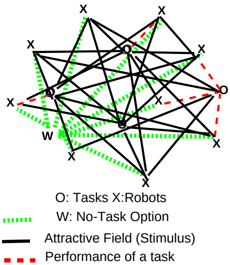


Figure: The attractive filed model (AFM)

Source nodes (o)	tasks to be allocated to agents
Agent nodes (x)	E.g., ants, humans, or robots
Black solid edges	attractive fields that correspond to an agent's perceived stimuli from each task
Green edges	attractive fields of no-task option shown as a particular task (w)
Red lines	not edges, but represent how each agent is allocated to a single task.

Properties of Agents under AFM

The probability of an agent choosing to perform a task:

$$P_j^i = \frac{S_j^i}{\sum_{j=0}^{J} S_j^i} \quad where, \quad S_0^i = S_{RW}^i \tag{1}$$

The strength of an attractive field varies according to the sensitivity of the agent is to that task, k_j^i, the distance between the task and the agent, d_{ij}, and the *urgency*, ϕ_j of the task.

$$S_j^i = tanh\{\frac{k_j^i}{d_{ij} + \delta}\phi_j\} \tag{2}$$

Delta distance δ, is a small constant, to avoid division by zero, in the case when a robot has reached to a task.

AFM and Self-organization

- Positive feedback through learning
  Example: Increasing task-sensitization of agents

$$If\ \ task\ \ is\ \ done:\ \ k_j^i \rightarrow k_j^i\ +\ k_{INC} \tag{3}$$

- Negative feedback through forgetting
  Exampel: Decreasing task-sensitization of agents

$$If\ \ task\ \ is\ \ not\ \ done:\ \ k_j^i \rightarrow k_j^i\ -\ k_{DEC} \tag{4}$$

- Multiple interactions through continuous flow of information.
- Randomness through stochastic task-selection.

Related issues for using AFM in real-world application

Figure: Modelling real-world application to a laboratory scenario

Map tasks & robot capabilities

1. workload ⇔ task-urgency
2. work done ⇔ task-urgency decrease
3. work pending ⇔ task-urgency increase

Enable continuous flow of info

1. Centralized communication
2. Local communication
3. Stigmergic communication

A Manufacturing Shop-Floor Interpretation of AFM

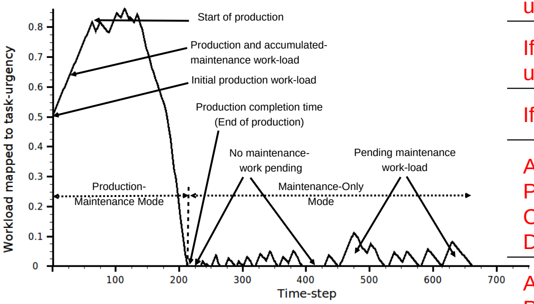


Figure: Production and maintenance cycle of a manufacturing shop-floor

Initial task urgency	workload x $\delta\phi_{INC}$
If task unattended	work-load increases by $\delta\phi_{INC}$
If task served	work-load decreases by $\delta\phi_{DEC}$
Average Production Completion Delay (APCD)	(*Ideal production time - Actual production time*)/ *Ideal production time*
Average Pending Maintenance Work (APMW)	(*Total pending maintenance work in all machines*)/*Total no. of machines.*

Centralized and Local Communication Models

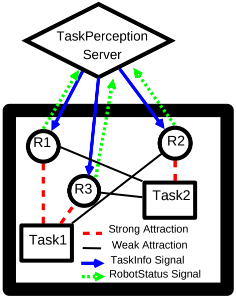


Figure: A centralized communication scheme

Centralized Model	Local Model
Global broadcast messaging	Local peer-to-peer messaging
Communicate synchronously	Communicate when peer(s) come in close contact (inside range r_{comm})
Modelled after *Polistes* wasps: global sensing no peer-to-peer communication	Modelled after *Polybia* wasps: local sensing local communication

Hybrid-event Driven Architecture on D-Bus

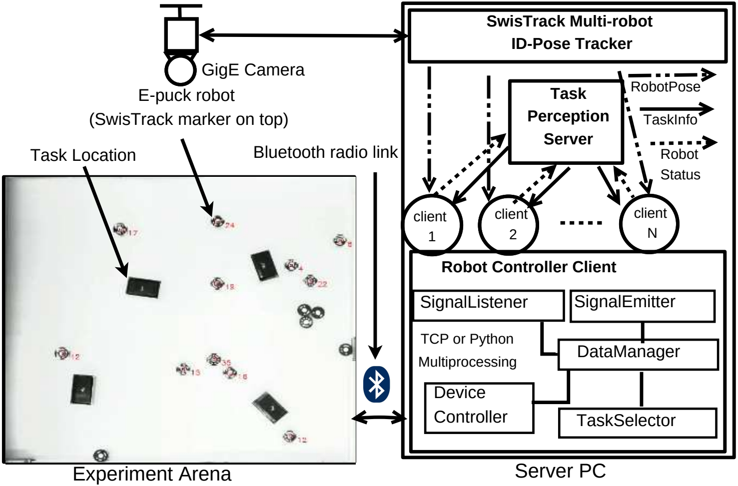
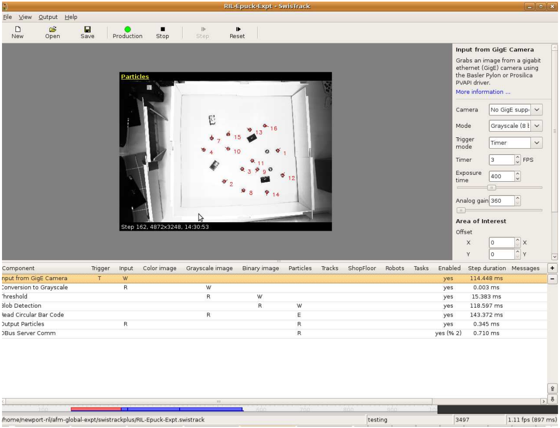
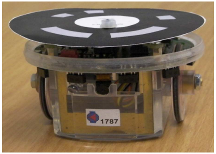


Figure: Hardware and software setup for centralized communication experiments

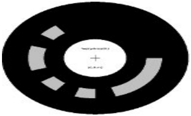
Tracking e-puck robots



(a) SwisTrack multi-robot tracker



(b) E-puck robot



(c) E-puck marker

Results: Shop-floor Work-load and Active Workers

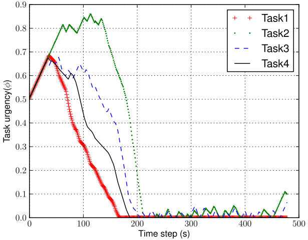


Figure: Changes in task-urgency

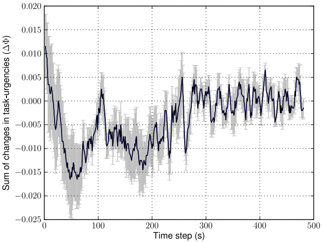


Figure: Shop-floor work-load

Shop-floor work-load:
Sum of changes in task-urgencies of all M tasks at $(q+1)^{th}$ step:

$$\Delta\Phi_{j,q+1} = \sum_{j=1}^{M}(\phi_{j,q+1} - \phi_{j,q}) \qquad (5)$$

Active worker ratio:

$$\frac{\textit{Active workers in all tasks}}{\textit{Total available workers}} \qquad (6)$$

Results: Shop-floor Work-load and Active Workers

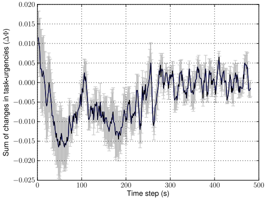


Figure: Shop-floor workload under CCM

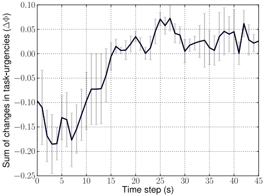


Figure: Shop-floor work-load under LCM

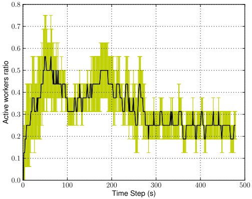


Figure: Active worker ratio under CCM

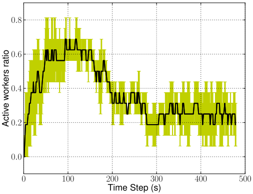


Figure: Active worker ratio under LCM

Results: Task-Performance

Table: Shop-floor production and maintenance task performance

Series	**APCD**	**APMW** (time-step)
A. Centralized communication, 8 robots, 2 tasks, 2 m^2 area	1.22	1
B. Centralized communication, 16 robots, 4 tasks, 4 m^2 area	2.3	3
C. Local communication, 16 robots, 4 tasks, 4 m^2 area, r_{comm}=0.5m	1.42	5
D. Local communication, 16 robots, 4 tasks, 4 m^2 area, r_{comm}=1m	1.46	2

Results: Task-specialization

Overall group task-specialization in terms of peak values of sensitization of all robots:

$$K^G_{avg} = \frac{1}{N}\sum_{i=1}^{N}\max_{j=1}^{M}\left(k^i_{j,q}\right) \tag{7}$$

Time-step values (q) taken to reach those peak values for all robots:

$$Q^G_{avg} = \frac{1}{N}\sum_{i=1}^{N} q^i_{k=k_{max}} \tag{8}$$

Table: Task-specialization values of the robots

Series	K^G_{avg} (SD)	Q^G_{avg} (SD)
A	0.40 (0.08)	38 (13)
B	0.30 (0.03)	18 (5)
C	0.39 (0.17)	13 (7)
D	0.27 (0.1)	11 (5)

Results: Energy-usage

Table: Sum of translations of robots in our experiments.

Series	Average translation (m)	SD
A. Centralized communication, 8 robots, 2 tasks, 2 m^2 area	2.631	0.804
B. Centralized communication, 16 robots, 4 tasks, 4 m^2 area	13.882	3.099
C. Local communication, 16 robots, 4 tasks, 4 m^2 area, r_{comm}=0.5m	4.907	1.678
D. Local communication, 16 robots, 4 tasks, 4 m^2 area, r_{comm}=1m	4.854	1.592

Results: Communication Loads

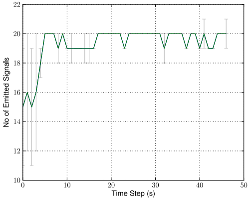


Figure: Frequency of `TaskInfo` signalling under Series A

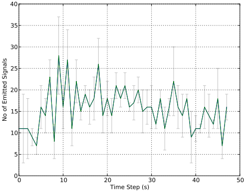


Figure: Frequency of `TaskInfo` signalling under Series C

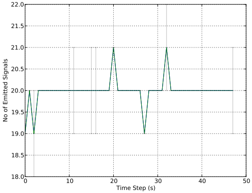


Figure: Frequency of `TaskInfo` signalling under Series B

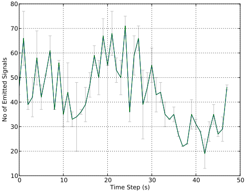


Figure: Frequency of `TaskInfo` signalling under Series D

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.