Self-regulated Multi-robot Task Allocation

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Outline

Background: The EPSRC Project: "Defying the rules - How Self Regulatory Social Systems Work"

Objectives

- Identify generic rules that allow social systems to develop sustainability through self-regulation.
- Improve the performance and robustness in the organization of social systems.

Our collaborators

- The Applied Mathematics Research Group, University of West of England
- The Centre for Systems Studies, University of Hull
- The Condensed Matter Theory Group, Imperial College, London

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 based, control theoretic.

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

[a] Parker, *J. of Phy. Agents*, 2:2, 2008
[b] Lerman *et. al*, *IJRR* 25, 2006

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[a].
- Cons: Difficult to design, implement, analyse and limited to one specific global task.[b].

[a] Pugh & Martinoli, *Swarm Intell:*3, 2009
[b] Gerkey & Mataric, *IJRR*, 23, 2004

Self-organization

What is Self-organization?

Pattern formation in both biological and physical systems through the local interactions internal to the system [a].

[a] Camazine *et al.*, Self-organization in Biological Systems, 2001.

Ingredients

- Positive feedback
  $\longrightarrow$ ants' recruitments to food source.
- Negative feedback
  $\longrightarrow$ overcrowding at food sources.
- Multiple interactions
  $\longrightarrow$ peer-to-peer, broadcast communication
- Randomness
  $\longrightarrow$ error in trail-following

Why Self-organized approach?

- Implementing simple agent behaviours is economical
- Easily scalable for large robot-teams and tasks
- Fault-tolerant
- Energy-efficient

Attractive Field Model (AFM)

Features of AFM

- Interdisciplinary: Developed from the study of ant, human and robotic social systems[a].
- Abstract: Sufficiently abstract to accommodate different sensing and communication models.

[a] Arcaute *et al.* Ecol. Complexity, 6:4 2008.

Requirements of Self-regulation

1. Concurrence: “The simultaneous presence of several tasks”
   $\longrightarrow$ at least a single task and the option of not doing any task.
2. Continuous flow of information:
   $\longrightarrow$ to perceive tasks and receive feedback on system performance.
3. Sensitization: “Individuals having different levels of preference”
   $\longrightarrow$ to all available tasks.
4. Forgetting: “A mechanism to reduce sensitisation levels”
   $\longrightarrow$ e.g. a slow general decay of sensitisation.

AFM as a Bipartite Network

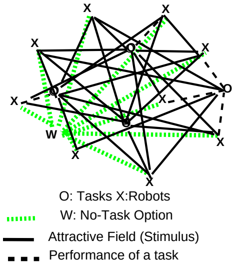

Figure: The attractive filed model (AFM)

Source nodes (o)	tasks to be allocated
Agent nodes (x)	agents 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 task (w)
Black dashed edges	not edges, but shows an agent allocated to a task.

Agent's probability to choose a task:

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

S_j^i and S_{RW}^i: i agent's stimuli to j task and random-walk.

Strength of an attractive field:

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

k_j^i, d_{ij}: i agent's sensitization and distance to task j. ϕ_j: urgency of task j.

AFM and Self-organization

- Positive feedback through learning
  Example: Increasing task-sensitization of agents
  With an agent's *rate of learning* tasks, k_{INC}:

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

- Negative feedback through forgetting
  Example: Decreasing task-sensitization of agents
  With an agent's *rate of forgetting* tasks, k_{DEC}:

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

- 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

Other issues

1. Enable learning/forgetting in controller
2. Perception of distance ⇔ localization

A Manufacturing Shop-Floor Interpretation of AFM

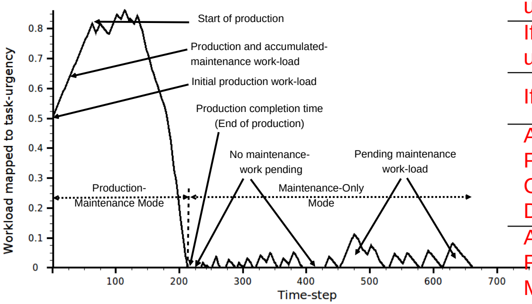

Figure: Production and maintenance cycles of a manufacturing shop-floor

AFM validation under a shop-floor scenario[a].

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.*

[a] Sarker & Dahl. *LNCS* 6234, 2010.

Centralized and Local Communication Models

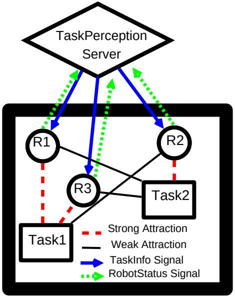

Figure: A centralized communication scheme

Communication models inspired by wasps[a]

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

[a] Jeanne. *Info. process. in social insects*, 1999

A Taxonomy of MRTA Solutions

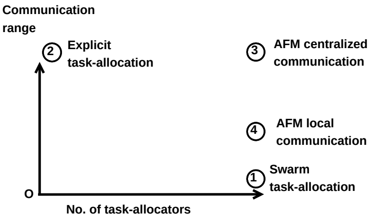

Figure: Classification of MRTA solutions based on task-allocation and communication strategies

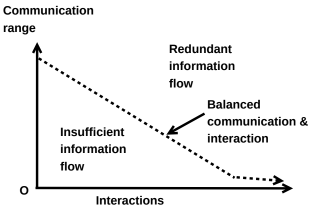

Figure: Information flow caused by different levels of communication and interaction

Multi-robot control architecture

Based on our Hybrid-event Driven Architecture on D-Bus[1]

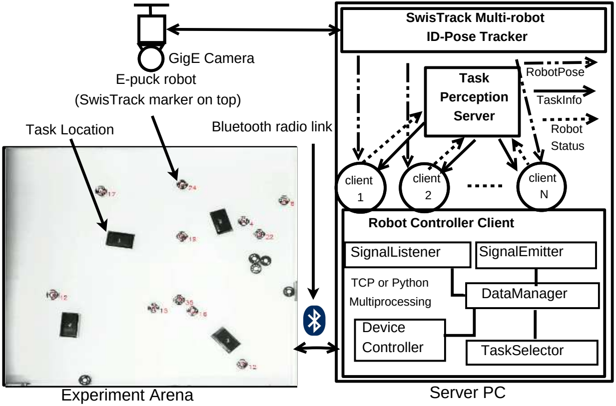

Figure: Hardware and software setup for centralized communication experiments

[1] Sarker & Dahl. *Proc. of UKACC Int'l Conference on Control, Coventry, UK* 2010.

Results: Shop-floor Work-load and Active Workers

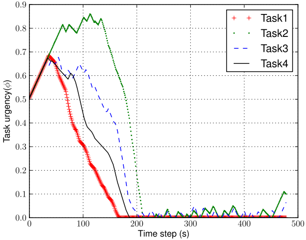

Figure: Changes in task-urgency

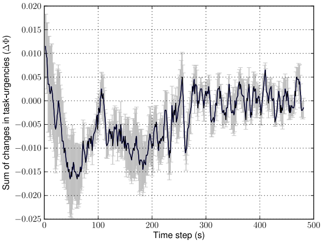

Figure: Shop-floor work-load

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 Ratio in 4 tasks experiments with 16 robots

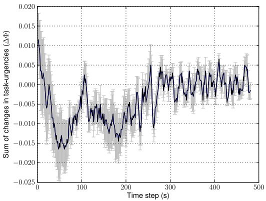

Figure: Shop-floor work-load under centralized comms.

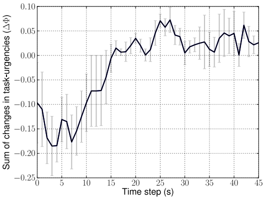

Figure: Shop-floor work-load under local comms.

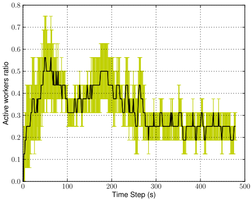

Figure: Active worker ratio under centralized comms.

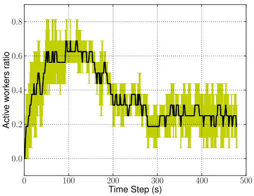

Figure: Active worker ratio under local comms.

Results: Task-Performance

Table: Shop-floor production and maintenance task performance

Experiment Series	*Production delay (SD) s*	*p-value* 1-tailed t-test (confidence)	*Pending maintenance time (SD) s*	*p-value* 1-tailed t-test
8 robots, 2 tasks, centralized, sample n=5	555 (50)	0.0	5 (5)	0.0
16 robots, 4 tasks, centralized, sample n=5	825 (360)	0.2 (60%)	15 (65)	0.0
16 robots, 4 tasks, local with range=0.5m, sample n=3	605 (180)	N/A	25 (85)	N/A
16 robots, 4 tasks, local with range=1m, sample n=3	615 (200)	0.0	10 (35)	0.0

Results: Task-specialization

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

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

Time spent to reach peak sensitization values for all robots:

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

Table: Task-specialization values of the robots

Experiment Series	K^G_{avg} (SD)	*p-value* 1-tailed t-test (confidence)	Q^G_{avg} (SD)	*p-value* 1-tailed t-test (confidence)
8 robots, 2 tasks, centralized, n=5	0.40 (0.08)	0.0	38 (13)	0.001 (99.8%)
16 robots, 4 tasks, centralized, n=5	0.30 (0.03)	0.2 (60%)	18 (5)	0.2 (60%)
16 robots, 4 tasks, local with range=0.5m, n=3	0.39 (0.17)	N/A	13 (7)	N/A
16 robots, 4 tasks, local with range=1m, n=3	0.27 (0.1)	0.0	11 (5)	0.0

Results: Energy-usage

Table: Sum of translations of robots in our experiments.

Experiment Series	Average translation (SD) m	*p-value* 1-tailed t-test (confidence)
8 robots, 2 tasks, centralized, n=5	2.631 (0.804)	N/A
16 robots, 2 tasks, centralized, n=5	13.882 (3.099)	0.001 (99.8%)
16 robots, 4 tasks, local with range=0.5m, n=3	4.907 (1.678)	N/A
16 robots, 4 tasks, local with range=1m, n=3	4.854 (1.592)	0.0

Results: Communication Loads in terms of Frequency of `TaskInfo` signalling

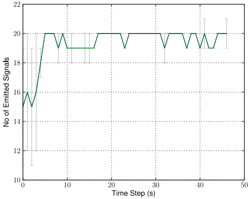

Figure: Under 8 robots, centralized communication

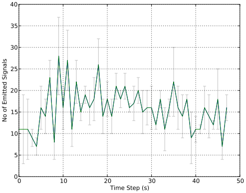

Figure: Under 16 robots, local communication, range=0.5m

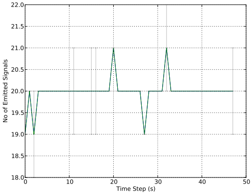

Figure: Under 16 robots, centralized communication

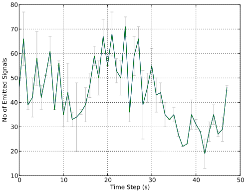

Figure: Under 16 robots, local communication range=1m

Conclusions & Future works

Conclusions

- AFM solves the MRTA issue for a relatively large group.
- Task-performance varies under different communication strategies
  $\rightarrow$ for a reasonably large group, local communication achieves similar task-performance and task-specialization comparing with a centralized counterpart, but *significantly* reduces motions.
- AFM can model complex multi-tasking environment
- Maximizing information flow may not be useful

Future works

- Deploy our task-allocation model in various task settings
- Relate communication range as a property of self-regulation
- Real-world implementation: e.g. warehouse automation

General Contributions

- Self-organization
  $\longrightarrow$ Self-organized allocation may produce specialized workers even when the group size is *small* (< 10), unlike assuming generalist workers prevents specialization in small groups[2].
- Task-allocation
  $\longrightarrow$ Local communication in task-allocation may outperform centralized one in terms of energy usage.
- System development
  $\longrightarrow$ Bottom-up de-coupled construction of *large* artificial system yields higher advantages particularly, flexibility and integration with inter-operable elements.

[2] Garnier *et al. Swarm Intelligence* 1:1, 2007.

Specific Contributions

- Interpreted AFM
  → as a basic mechanism for multi-robot task-allocation
- Validated the effectiveness of AFM
  → with reasonably *large* number of real robots
- Compared centralized & local communication in MRTA
  → modelled after social wasps: *Polistes* and *Polybia*
- Developed a *flexible* multi-robot control architecture
  → using *D-Bus* inter-process communication
- Classified MRTA solutions focusing three major issues:
  1. Organization of task-allocation
  2. Communication and
  3. Interaction