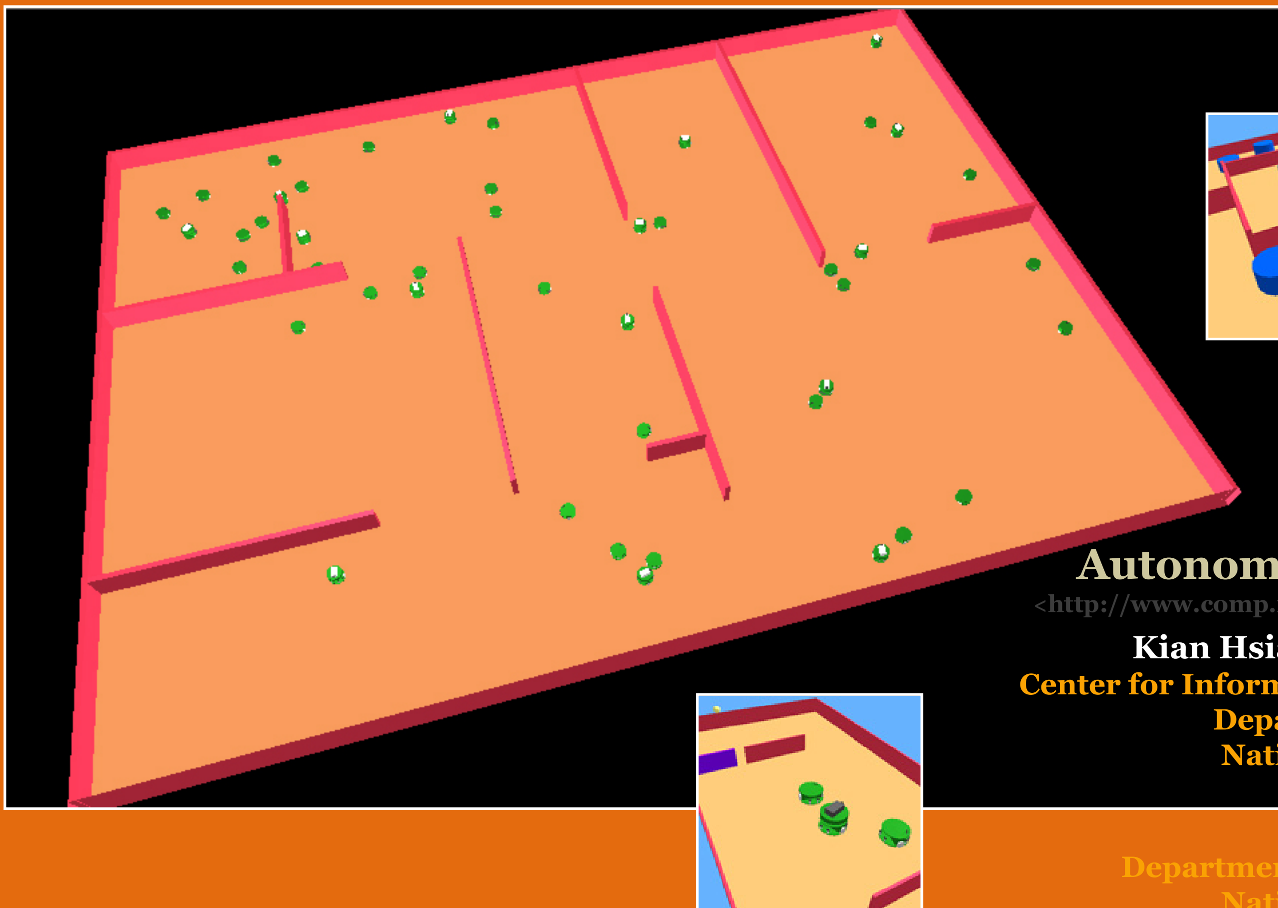
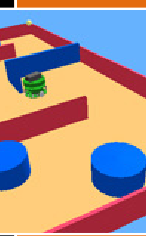
NITA Project ID: G9

Task Allocation via Self-Organizing Swarm Coalitions in Distributed Mobile Sensor Network





Autonomous Robotics Group
<http://www.comp.nus.edu.sg/~lowkh/research.html>

Kian Hsiang Low, Wee Kheng Leow
Center for Information Mining and Extraction
Department of Computer Science
National University of Singapore
lowkh, leowwk@comp.nus.edu.sg

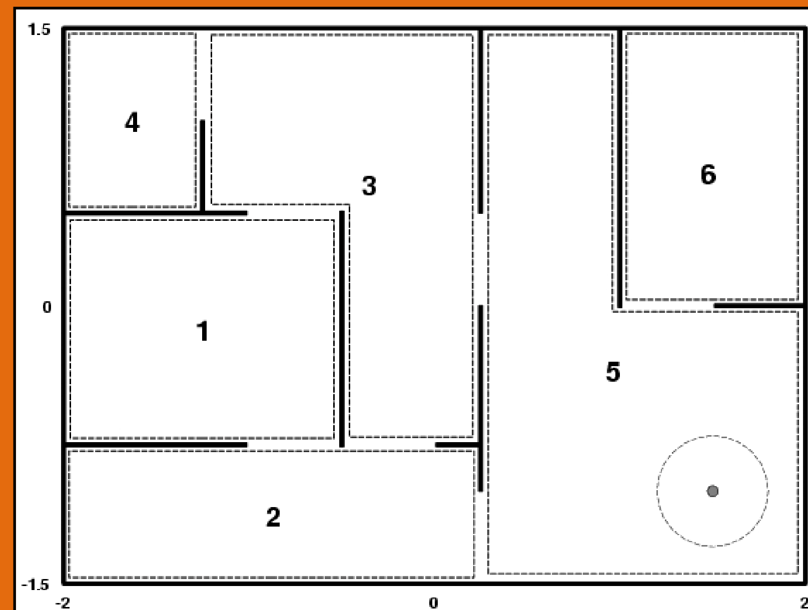
Marcelo H. Ang, Jr.
Department of Mechanical Engineering
National University of Singapore
mpeangh@nus.edu.sg

Problem Definition

Sparse Network Coverage in Dynamic, Unpredictable Environments

If we define v_i as the region visible to mobile sensor i, then the maximum region covered by the sensor network is much less than the bounded region U to be observed, i.e.,

$$\bigcup_i v_i << U$$



A 4m by 3m environment that is divided into 6 regions. The circle at the bottom right represents the robot's sensing radius of 0.3m. The environment is 42.44 times larger than the robot sensing area.

This situation arises due to

1. no prior information on target locations, densities or motion patterns;
2. limited sensory range;
3. very large area to be observed.

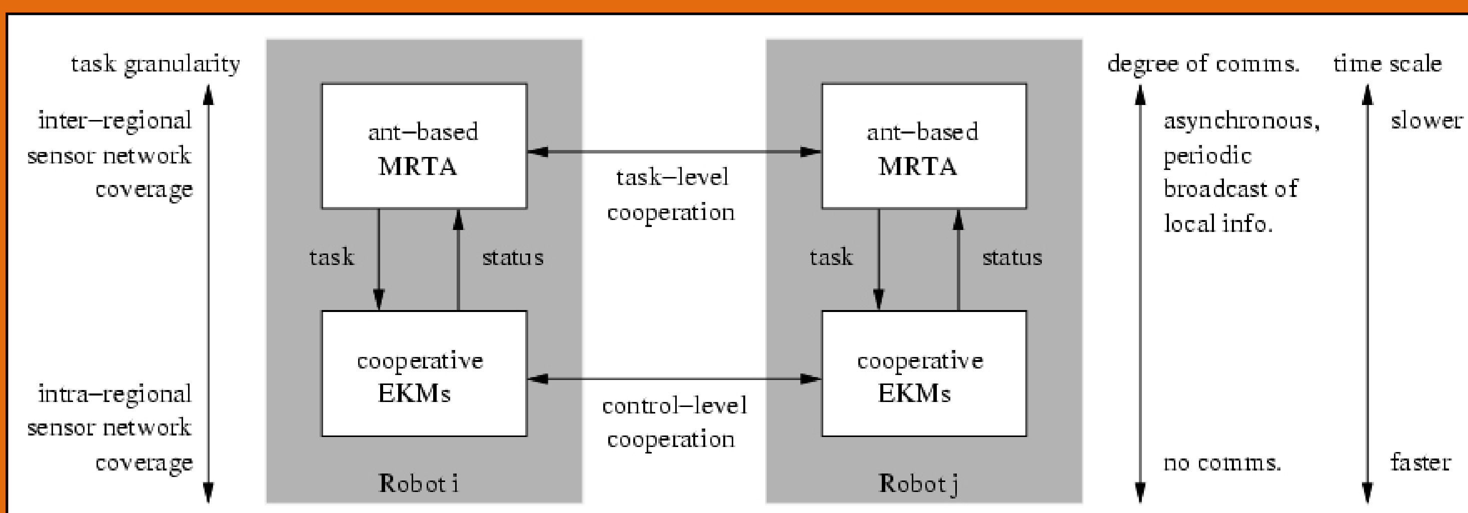
All these factors discourage static sensor placements or uninformed mobility (e.g., random motion or patrol). Informed, intelligent mobility is desired.

Proposed Methodology

Two-Level Integrated Architecture for Resource-Bounded Multi-Robot Cooperation

Multi-Robot Task Allocation (MRTA) via Self-Organizing Swarm Coalitions : "Coverage Problem is Discretized"
Use swarm intelligence principles to self-organize the robot coalitions in a decentralized manner according to the distributions of targets across regions.

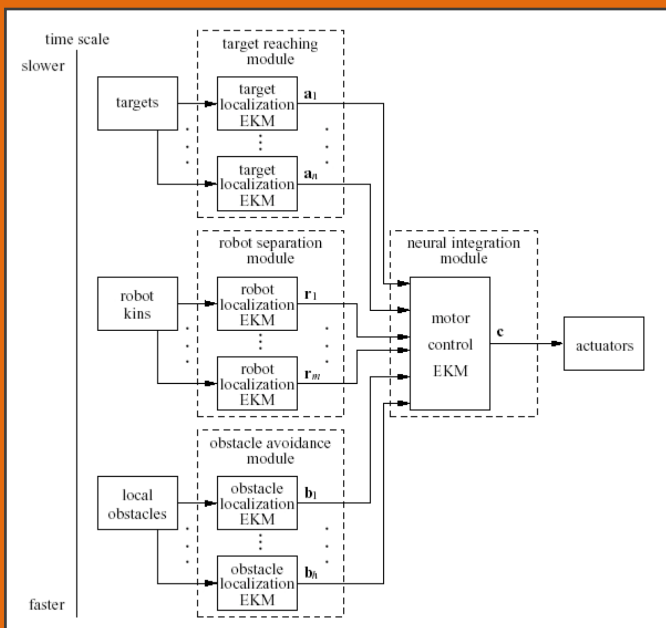
Motion Control via Cooperative Extended Kohonen Maps (EKMs) : "Coverage Problem is Continuous"
Use self-organizing neural network ensemble to coordinate behaviors (i.e., track detected targets in a region, repel robots to maximize coverage, avoid obstacles, and navigate between regions).



Cooperative EKMs
Behavioral Coordination Mechanism

The robot's action selection capability is significantly enhanced by

- self-organization of continuous state and action spaces to provide smooth, efficient and fine motion control, and
- behavioral coordination via the cooperation and competition of EKMs to achieve more complex single- and multi-robot motion tasks.



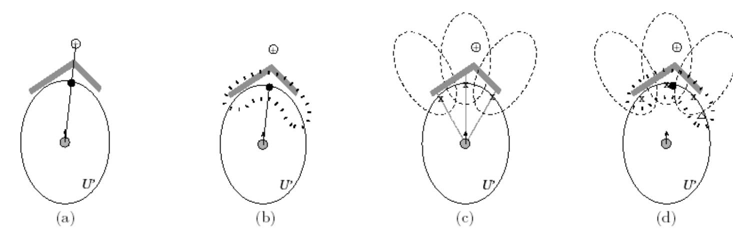


Figure 2: Cooperative EKMs. (a) In response to the target ⊕, the nearest neuron (black dot) in the target localization EKM (ellipse) of the robot (gray circle) is activated. (b) The activated neuron produces a target field (dotted ellipse) in the motor control EKM. (c) Three of the robot's sensors detect obstacles and activate three neurons (crosses) in the obstacle localization EKMs, which produce the obstacle fields (dashed ellipses). (d) Subtraction of the obstacle fields from the target field results in the neuron at △ to become the winner in the motor control EKM, which moves the robot away from the obstacle.

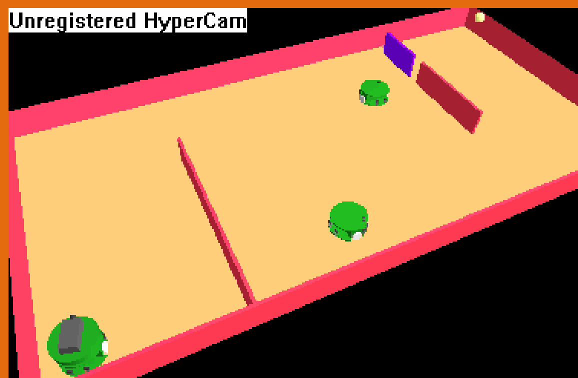
Selected Publications

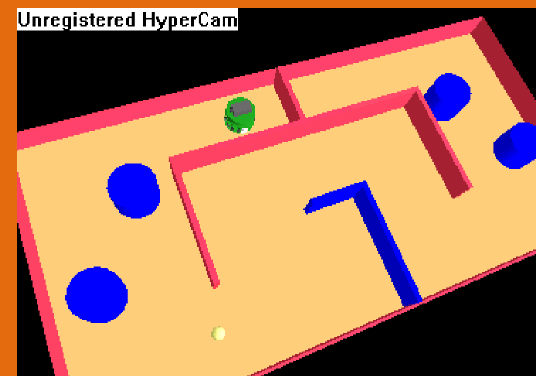
Kian Hsiang Low, Wee Kheng Leow & Marcelo H. Ang, Jr (2002). **A Hybrid Mobile Robot Architecture with Integrated Planning and Control**. In *Proceedings of 6th International Conference on Autonomous Agents (ICAA-02)*, pages 219-226.

Kian Hsiang Low, Wee Kheng Leow & Marcelo H. Ang, Jr (2003). **Action Selection for Single- and Multi-Robot Tasks Using Cooperative Extended Kohonen Maps**. In *Proceedings of 18th International Joint Conference on Artificial Intelligence (IJCAI-03)*, pages 1505-1506.

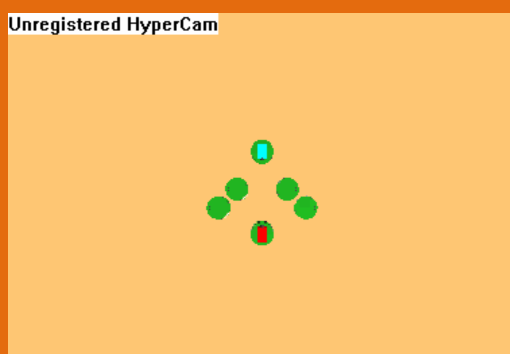
Cooperative EKMs
Test Results

Single Robot Motion in Complex, Unpredictable Environments





Cooperative Multi-Robot Tracking of Multiple Moving Targets



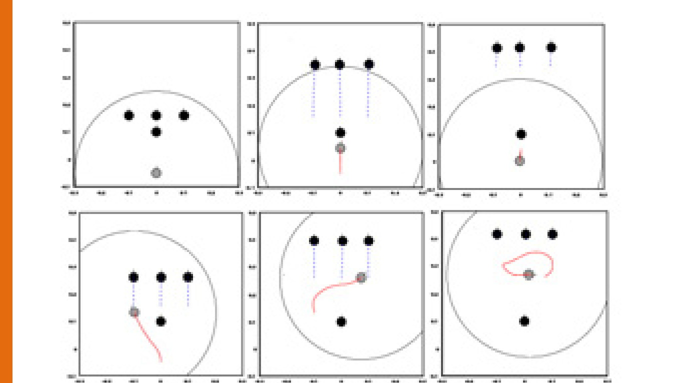


Figure 4: (Top row) Robot (gray) using action superposition ASM got stuck at the stationary target. Eventually, the three mobile targets moved out of the robot's sensing range (circle). (Bottom row) Robot using cooperative EKMs could negotiate past the stationary target to track all the targets.

Ant-Based MRTA
Self-Organization of Coalitions

Issues Addressed

- **Task Allocation for Multi-Robot Tasks**
  Existing algorithms (e.g., auction- and behavior-based) assume *a multi-robot task can be partitioned into single-robot tasks*. But this may not be always possible or the multi-robot task can be more efficiently performed by coalitions of robots.

- **Coalition Formation for Minimalist Robots**
  Existing coalition formation schemes require *complex planning, explicit negotiation, and precise estimation of coalitional cost*. Hence, they do not perform well in dynamic, real-time scenarios.

- **Cooperation of Resource-Limited Robots**
  Robots with *limited communication and sensing* capabilities (i.e., partial observability) can only obtain local, uncertain information of the dynamic environment. With *limited computational power*, their cooperative strategies cannot involve complex planning or negotiations.

Ant-Based MRTA
Self-Organization of Coalitions

“Go to the Ant”: Principles from Swarm Intelligence

Such a decentralized system benefits from increased robustness, scalability, security, and adaptability to environmental changes.

- **Encounter Pattern Based on Waiting Time**
  Encounter patterns provide a simple, local cue for ants with sensory and cognitive limitations to track regional densities of ants and objects of interest >>> *Predict target and robot density in a region.*
- **Self-Organization of Social Dominance**
  The division of labor in an ant colony is strongly influenced by its social dominance order, which self-organizes to match the task demands of the colony & changing environment >>> *Less dominant robots leave a region.*
- **Dynamic Task Allocation**
  The task allocation in ants can efficiently arrange the ants in proportion to the amount of work in the changing environment >>> *Self-organize robot coalitions according to target distributions across regions.*

Selected Publication

Kian Hsiang Low, Wee Kheng Leow & Marcelo H. Ang, Jr (2004). **Task Allocation via Self-Organizing Swarm Coalitions in Distributed Mobile Sensor Network**. To appear in *Proceedings of 19th National Conference on Artificial Intelligence (AAAI-04).*

Ant-Based MRTA
Test Results

Environment Setup

Network coverage of 30 randomly moving targets with 5, 10, and 15 mobile sensors in built-up area (page 2).

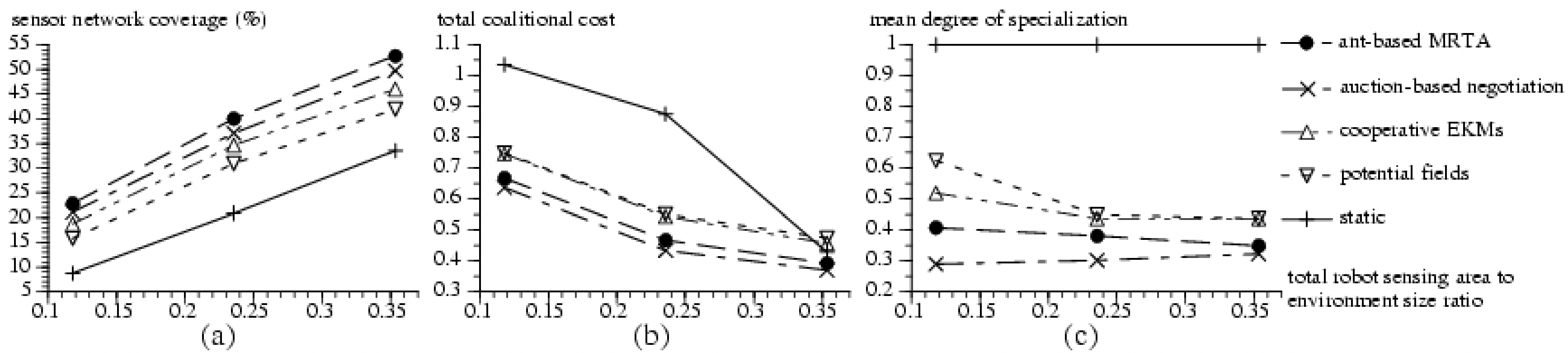


Figure 2: Comparison of performance using different motion control and task allocation strategies: (a) Sensor network coverage, (b) total coalitional cost, and (c) mean degree of specialization.

Auction-based negotiation[1] between coalition leaders

1. more information (exact number of targets and robots in each region and task performance of these robots);
2. longer communication range;
3. more complex, synchronous negotiation

[1]It can be entirely replaced by a *centralized coordinator*, which requires even more resources.

With evasive targets, coverage of 15 static sensors drops to 10%.