

A game theoretic model for management of mobile sensors

Presented by: **Ronnie Johansson**

Co-authors: **Ning Xiong** and **Henrik I. Christensen**

CAS (centre for autonomous systems), the Royal institute of Technology (**KTH**), Stockholm, Sweden

The work was financially supported by the Swedish defence research agency (**FOI**)



Primary objectives of current work

Study effects of multi-target tracking with mobile sensors using a game theory based algorithm

Previous properties: stationary sensors negotiating about a partitioning of the set of targets.

Now:

- Sensors are mobile
- Sensors have limited resources
- Targets are shared

Primary objectives of current work

Study effects of multi-target tracking with mobile sensors using a game theory based algorithm

Previous properties: stationary sensors negotiating about a partitioning of the set of targets.

Now:

- Sensors are mobile
- Sensors have limited resources
- Targets are shared

Primary objectives of current work

Study effects of multi-target tracking with mobile sensors using a game theory based algorithm

Previous properties: stationary sensors negotiating about a partitioning of the set of targets.

Now:

- Sensors are mobile
- Sensors have limited resources
- Targets are shared

Primary objectives of current work

Study effects of multi-target tracking with mobile sensors using a game theory based algorithm

Previous properties: stationary sensors negotiating about a partitioning of the set of targets.

Now:

- Sensors are mobile
- Sensors have limited resources
- Targets are shared

Results

Intermediate (i.e., current)

- A framework for studying negotiation-based target-to-sensor allocation
- Forced target sharing yields robustness to sensor failures
- Simultaneous consideration of multiple objectives allow sensors to escape situations where a greedy approach gets “stuck”

Sensor agent negotiation

Previous work: Negotiation offers:

- complete allocation of sensors to targets
- every allocation had a value for every sensor (*reward*)
- the *negotiation utility* dependent on time and reward

Sensor agent negotiation

Previous work: Negotiation offers:

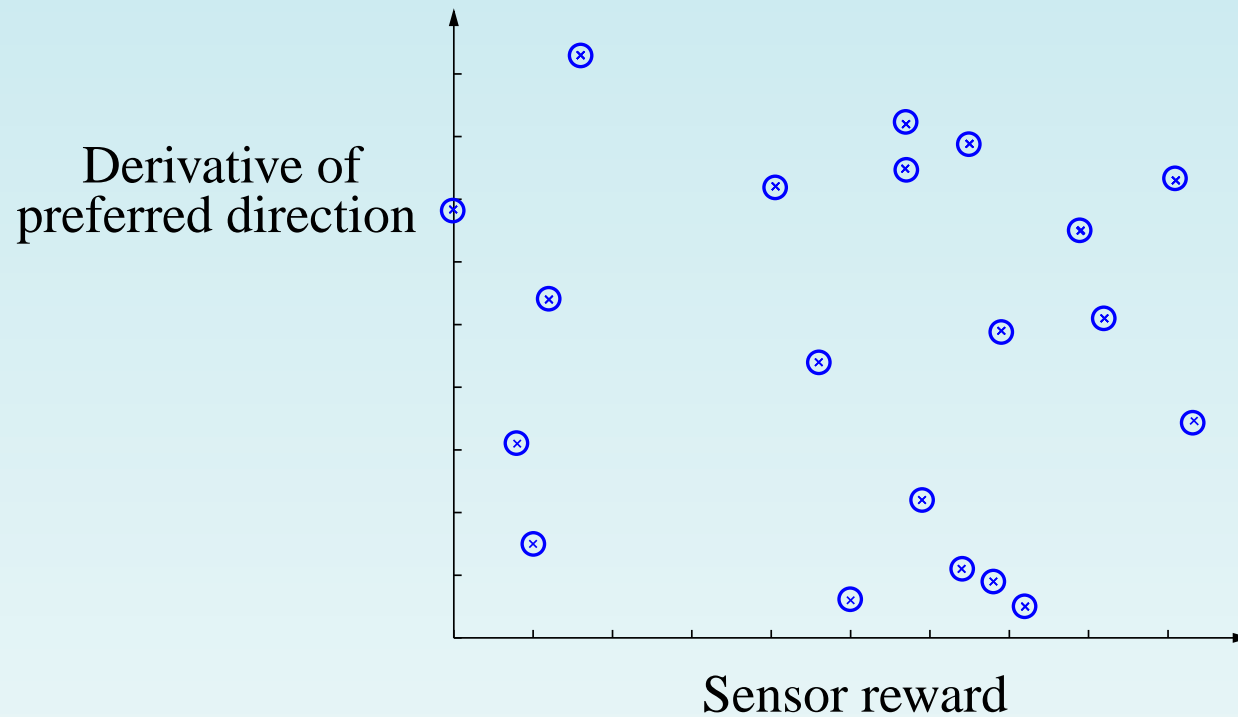
- complete allocation of sensors to targets
- every allocation had a value for every sensor (*reward*)
- the *negotiation utility* dependent on time and reward

Current work:

- offers are still target-to-sensor allocations, but may be overlapping
- every allocation has two associated values, reward and reward derivative
- the negotiation utility still depends on time

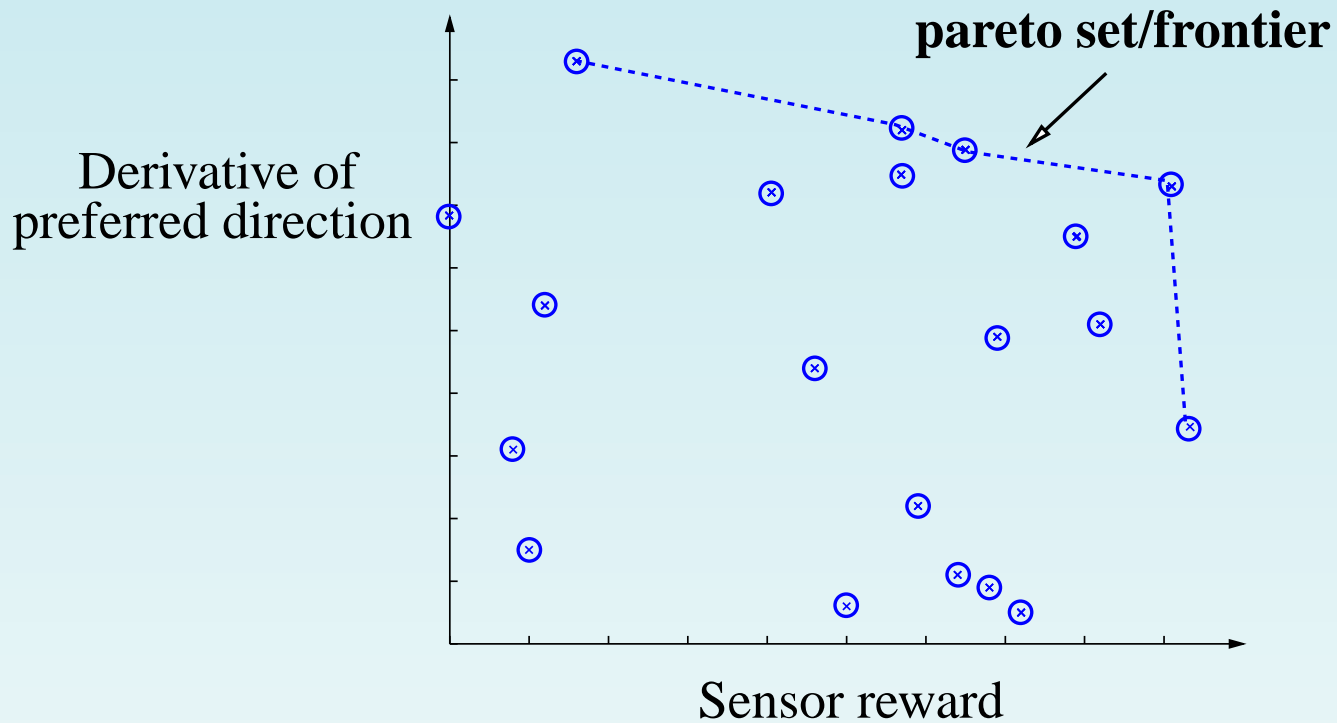
Dominance

Evaluation of offers for some sensor agent i



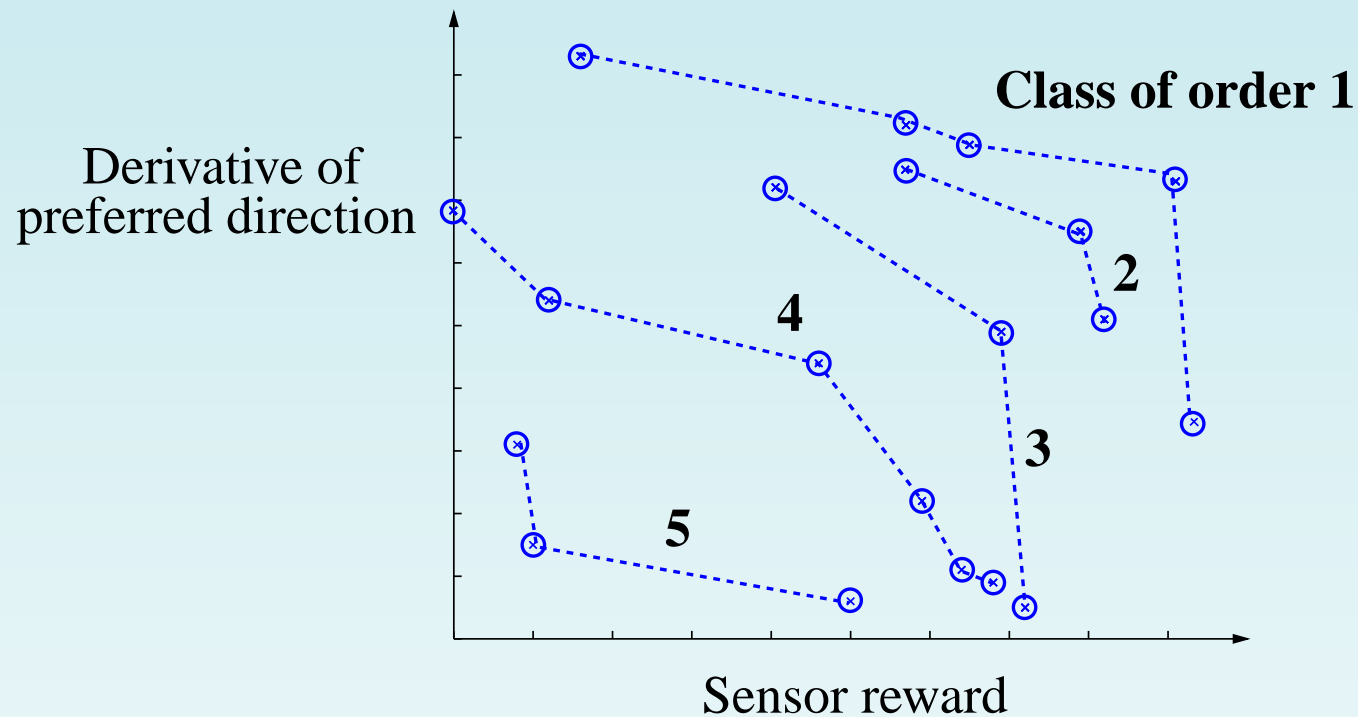
Dominance

Evaluation of offers for some sensor agent i



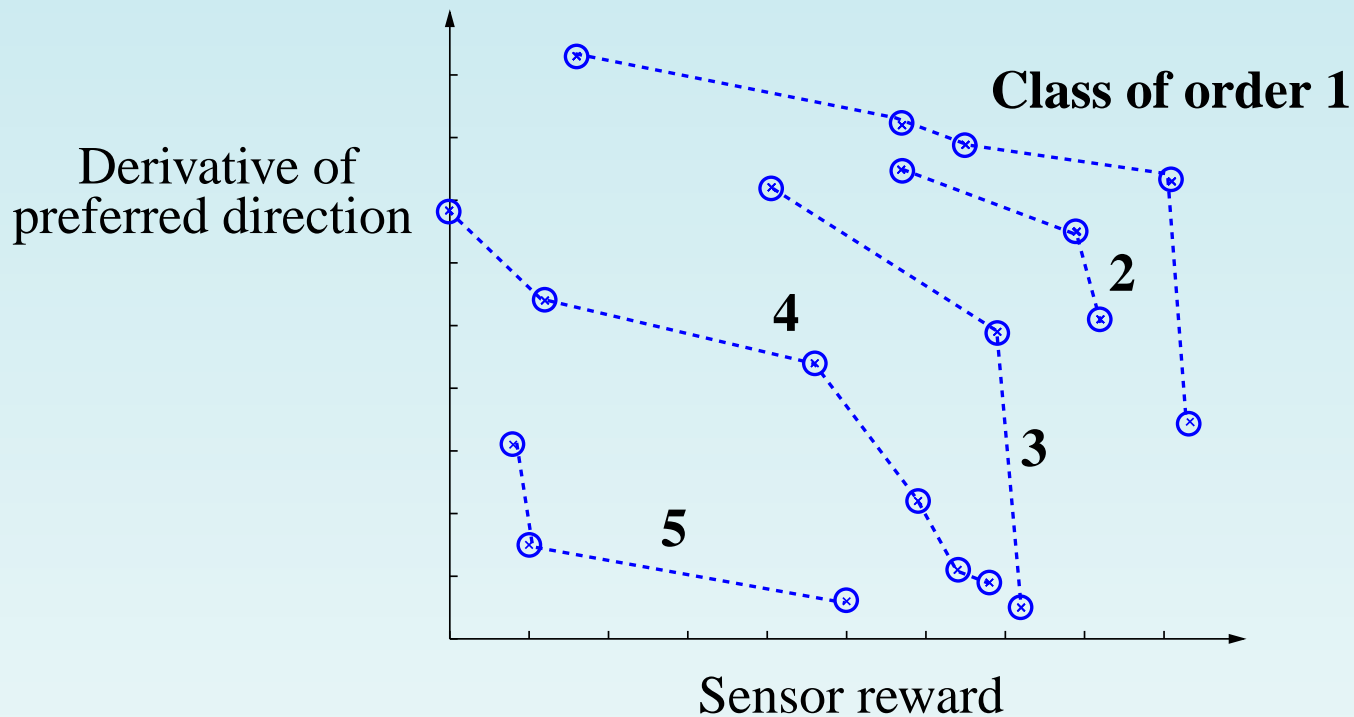
Dominance

Evaluation of offers for some sensor agent i



Dominance

Evaluation of offers for some sensor agent i



$$U_i(o, \mathbf{t}) = f(\text{order}_i(o), \mathbf{t}) = -\text{order}_i(o) - \mathbf{t}$$

Sensor reward

Individual *sensor measurement reward* for sensor i

$$r_i^m(D_i) \triangleq \sum_{j \in D_i} \gamma_{ij} \cdot r_j(S_j)$$

D_i is the set of targets tracked by sensor i and S_j the set of sensors tracking target j .

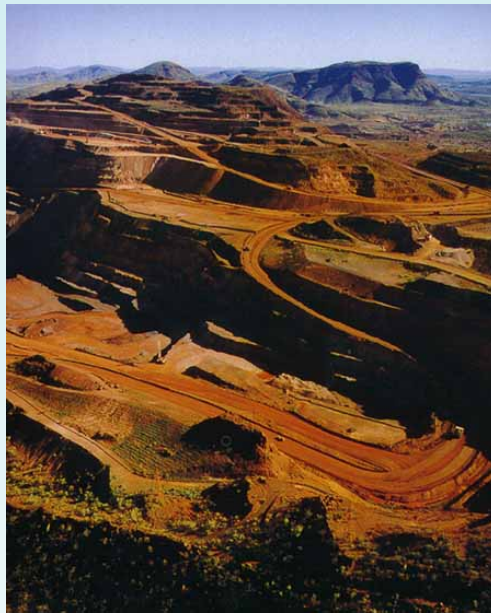
Net reward (the reward which is considered in the negotiations)

$$r_i^{net}(D_i) \triangleq \alpha_i + (1 - \alpha_i)r_i^m(D_i), \quad 0 \leq \alpha_i \leq 1 ,$$

For the reward on every target in our experiments, we use the *information gain* from Kalman filtering.

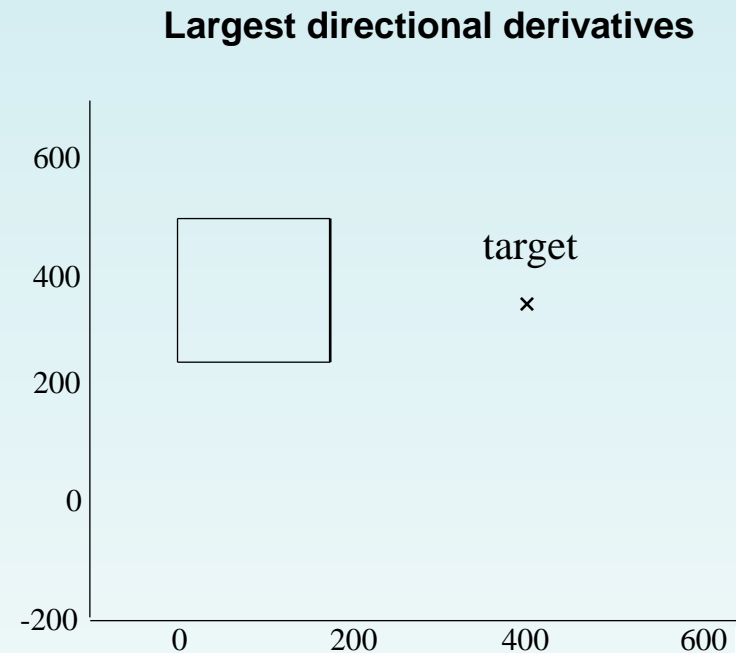
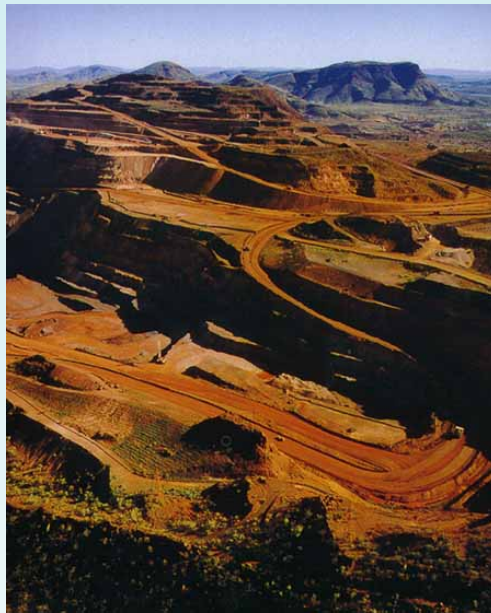
Derivative of preferred direction

A terrain function, $t(\mathbf{p}, \mathbf{e}_\theta)$, discounts the derivatives for any tuple of position \mathbf{p} and any direction \mathbf{e}_θ . The preferred direction has the highest discounted derivative, $\max_{\mathbf{e}_\theta} \{t(\mathbf{p}, \mathbf{e}_\theta) \cdot r'_{\mathbf{e}_\theta}\}$.



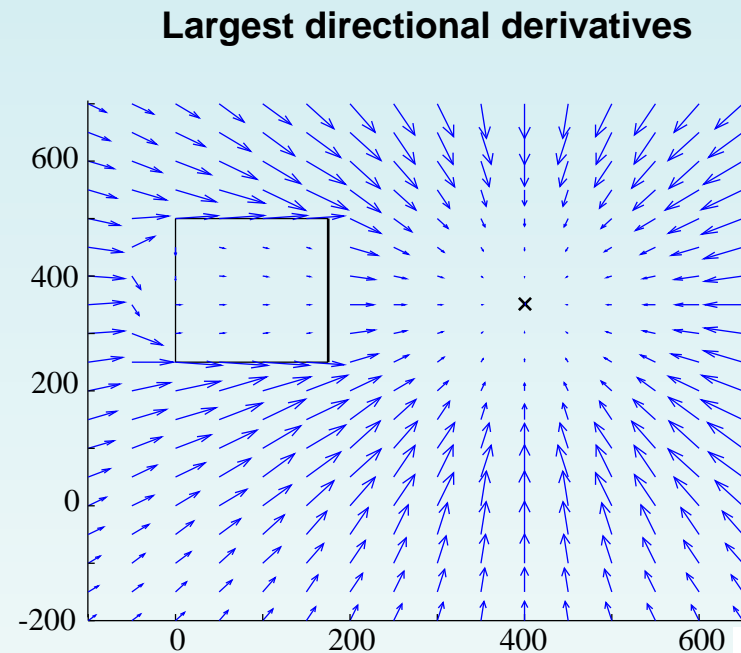
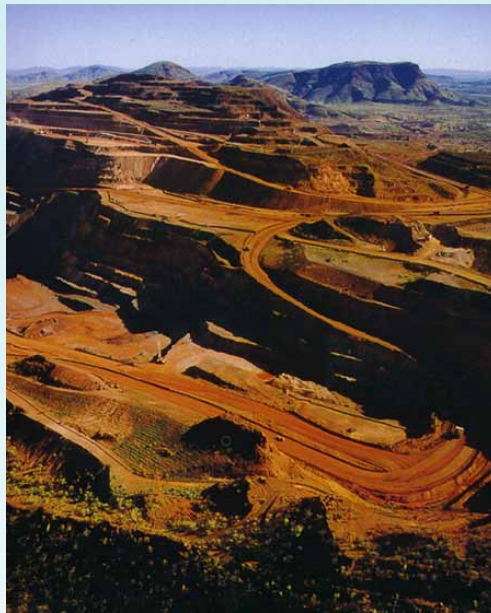
Derivative of preferred direction

A terrain function, $t(\mathbf{p}, \mathbf{e}_\theta)$, discounts the derivatives for any tuple of position \mathbf{p} and any direction \mathbf{e}_θ . The preferred direction has the highest discounted derivative, $\max_{\mathbf{e}_\theta} \{t(\mathbf{p}, \mathbf{e}_\theta) \cdot r'_{\mathbf{e}_\theta}\}$.



Derivative of preferred direction

A terrain function, $t(\mathbf{p}, \mathbf{e}_\theta)$, discounts the derivatives for any tuple of position \mathbf{p} and any direction \mathbf{e}_θ . The preferred direction has the highest discounted derivative, $\max_{\mathbf{e}_\theta} \{t(\mathbf{p}, \mathbf{e}_\theta) \cdot r'_{\mathbf{e}_\theta}\}$.



Experiment setting

- We implement an allocation strategy based on the negotiation algorithm, called the N-tracker.
- We also implement a reference strategy, called the G-tracker.
- Trackers are run independently on three scenarios, including a set of mobile sensors and a set of targets.
- With regular time intervals both trackers reconsider the target-to-sensor assignment.

Experiment setting

- We implement an allocation strategy based on the negotiation algorithm, called the N-tracker.
- We also implement a reference strategy, called the G-tracker.
- Trackers are run independently on three scenarios, including a set of mobile sensors and a set of targets.
- With regular time intervals both trackers reconsider the target-to-sensor assignment.

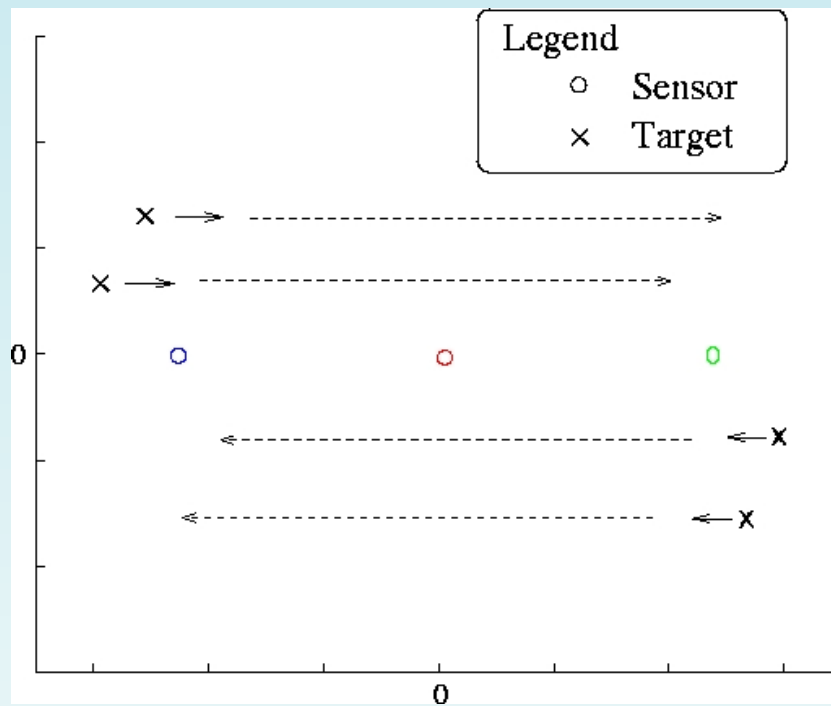
Experiment setting

- We implement an allocation strategy based on the negotiation algorithm, called the N-tracker.
- We also implement a reference strategy, called the G-tracker.
- Trackers are run independently on three scenarios, including a set of mobile sensors and a set of targets.
- With regular time intervals both trackers reconsider the target-to-sensor assignment.

Experiment setting

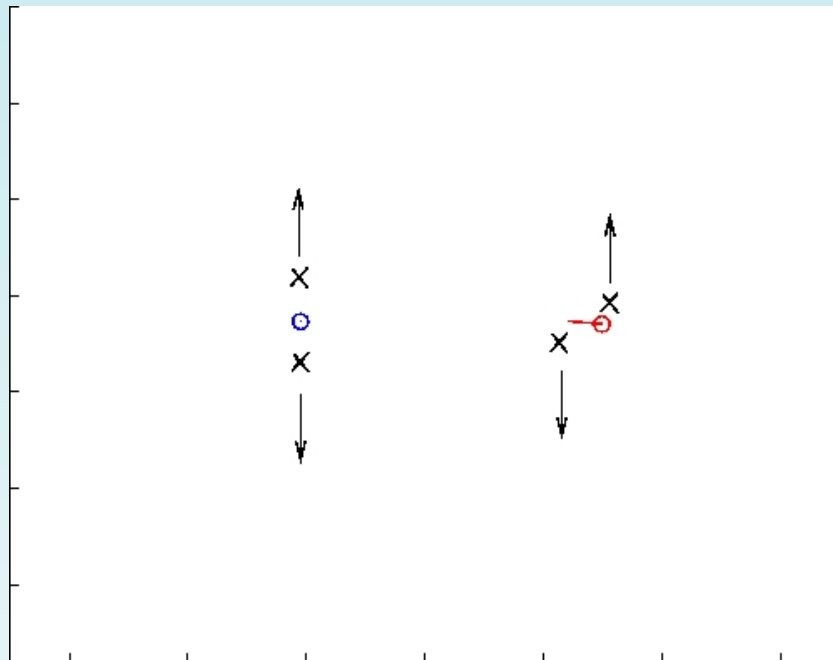
- We implement an allocation strategy based on the negotiation algorithm, called the N-tracker.
- We also implement a reference strategy, called the G-tracker.
- Trackers are run independently on three scenarios, including a set of mobile sensors and a set of targets.
- With regular time intervals both trackers reconsider the target-to-sensor assignment.

Scen1: Tracking four targets

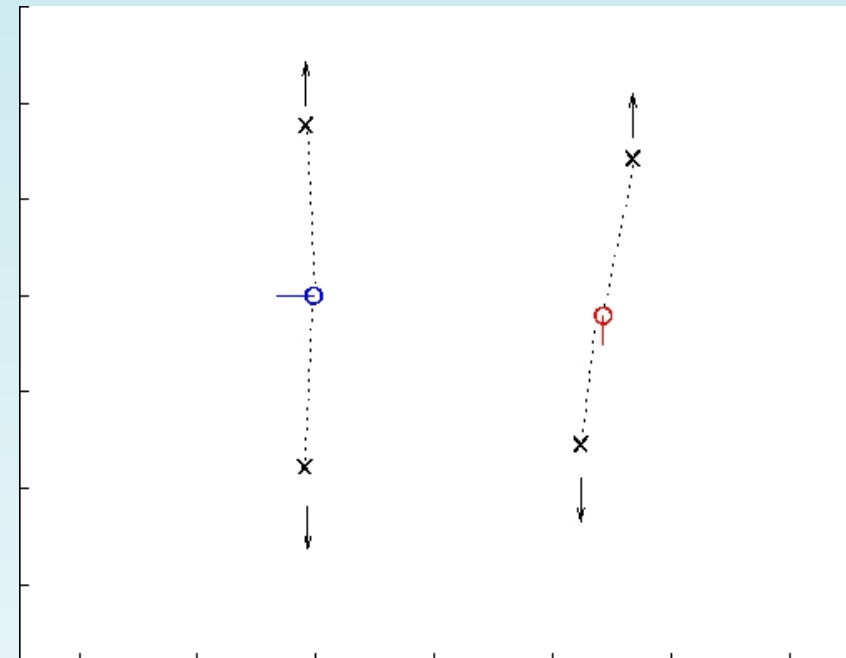


	G-tracker	N-tracker	Relative
Reward	3.7372	3.3765	0.90
Lost targets	1.1830	0.8693	0.73

Scen2: G-tracker getting stuck

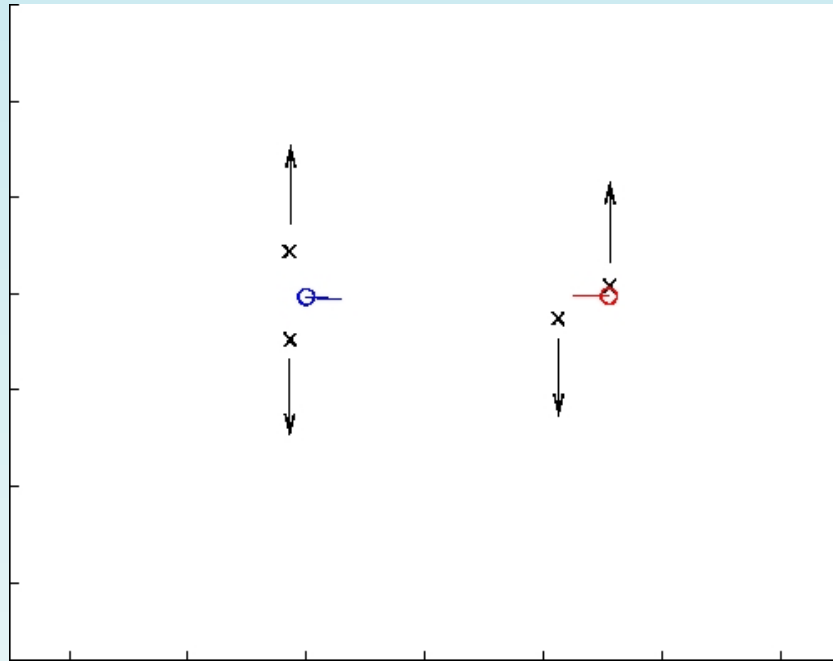


Initially

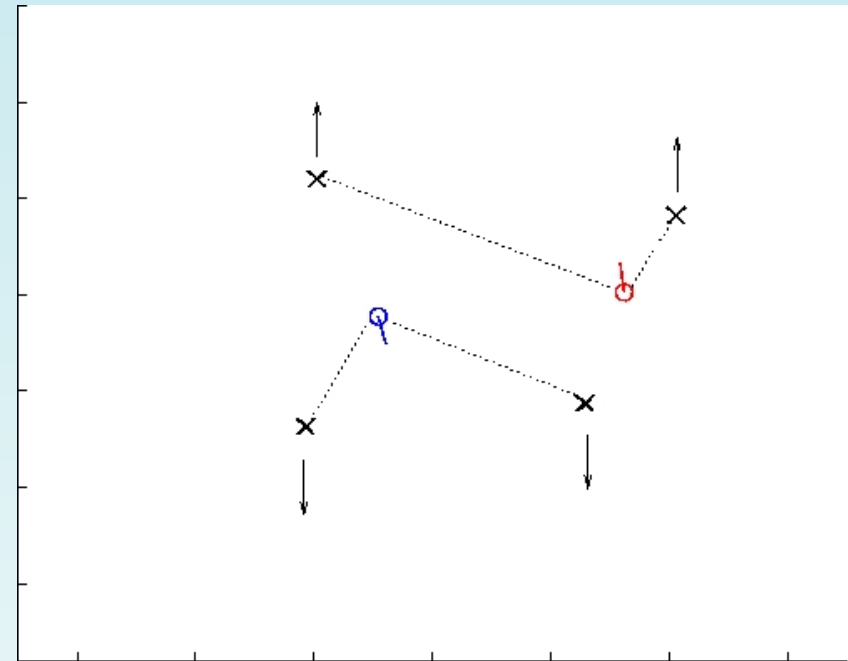


After some time

Scen2: N-tracker eluding deadlock

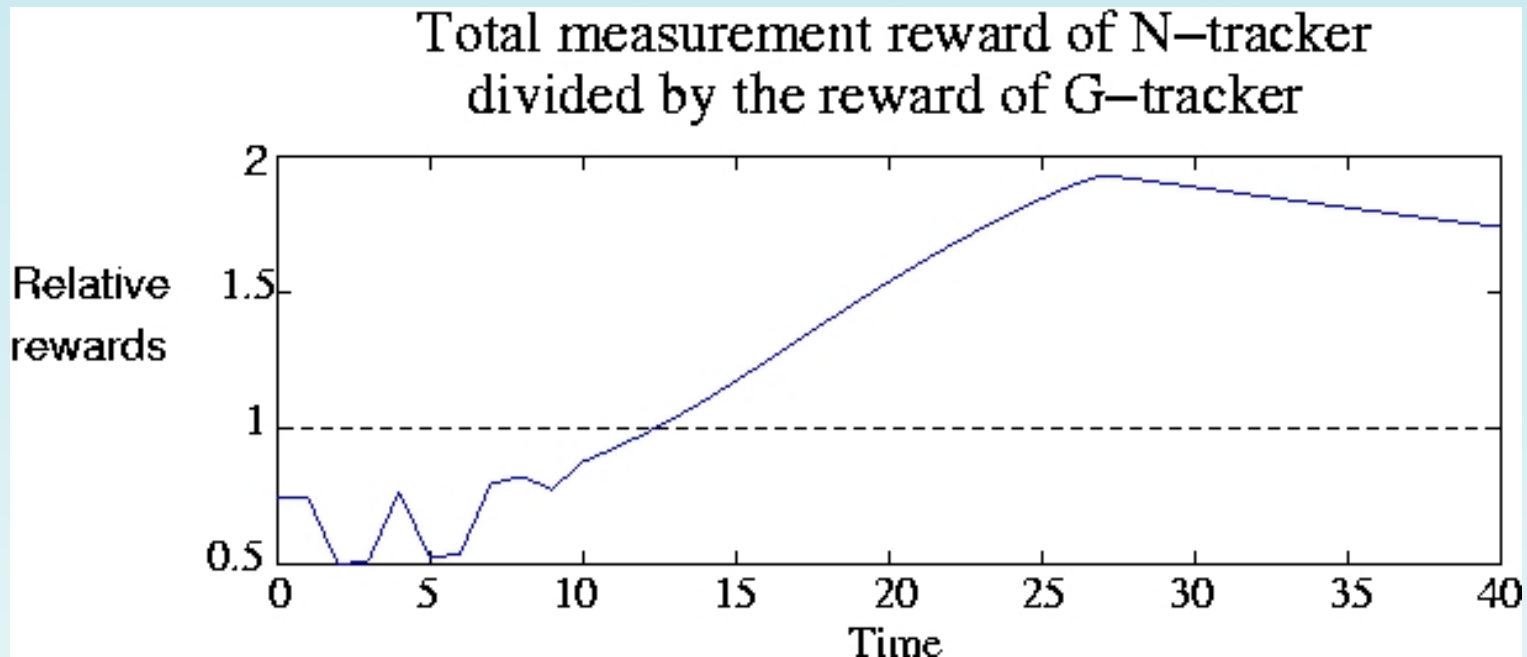


Initially



After some time

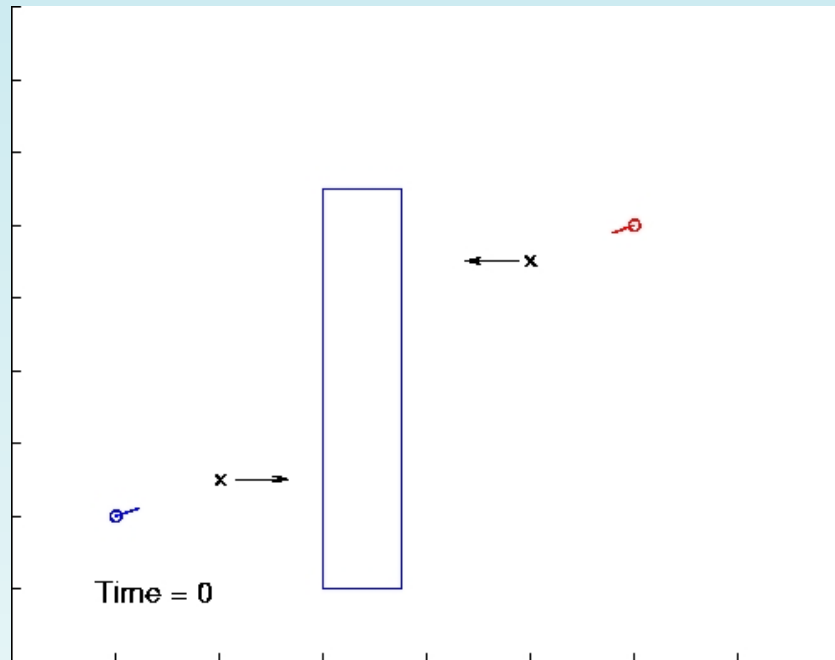
Scen2: Results



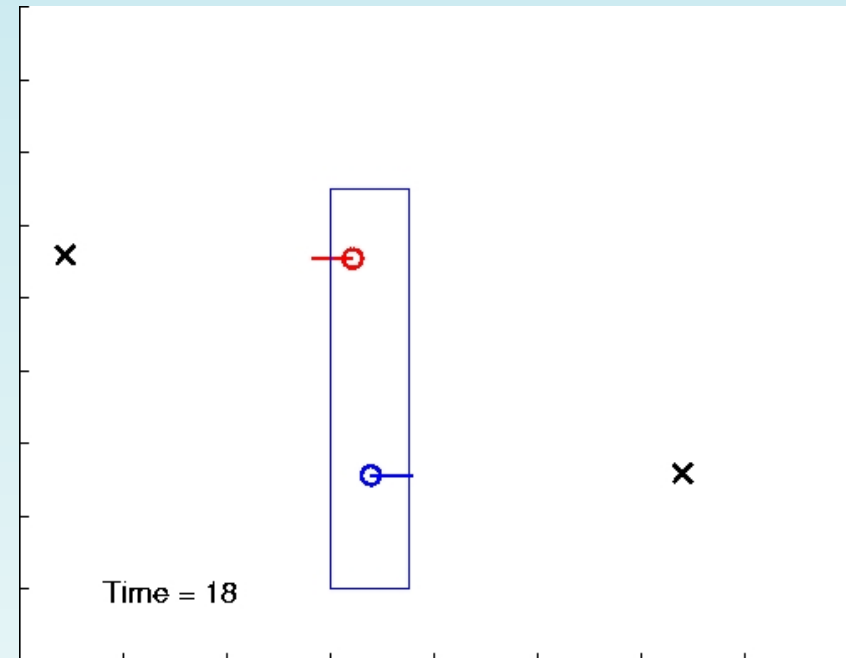
At $t = 10$: The N-tracker settles on which targets to track

At $t = 27$: The G-tracker escapes its deadlock

Scen3: G-tracker in bad terrain

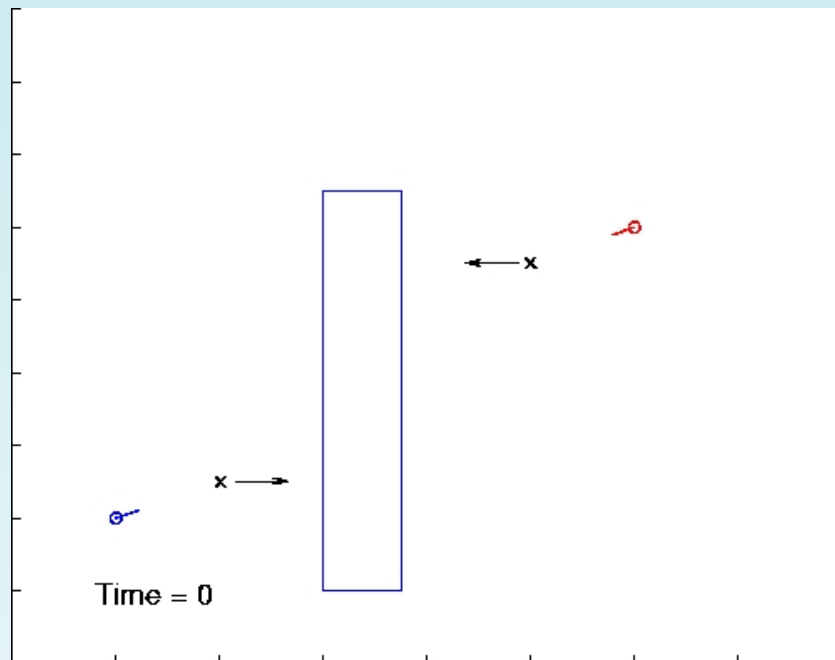


Initially

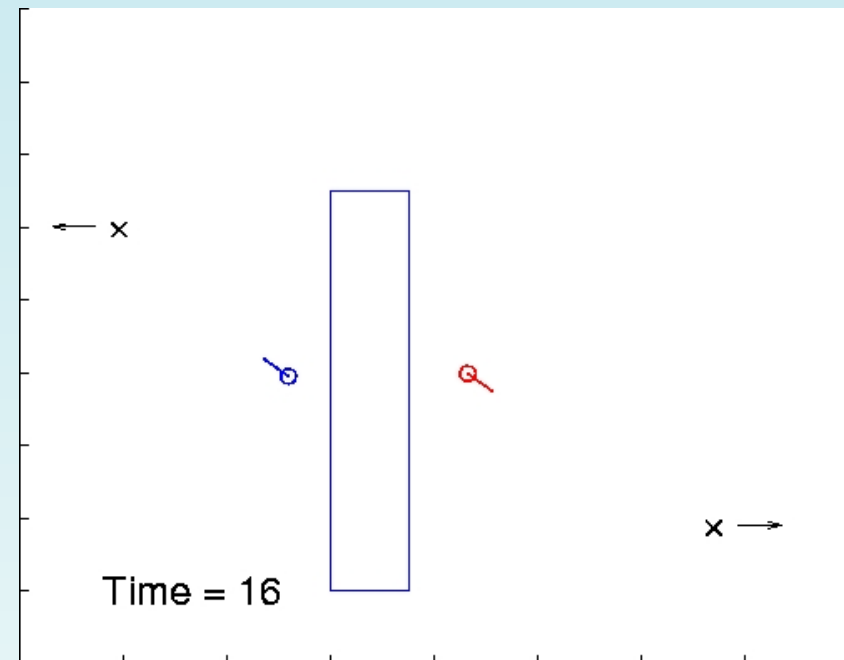


After some time

Scen3: N-tracker switches targets



Initially



After some time

Summary and future work

- We have developed a framework for studying negotiation-based sensor management with mobile sensors
- Results indicate that the negotiation-based strategy (the N-tracker) has advantages over a greedy one (the G-tracker).

Summary and future work

- We have developed a framework for studying negotiation-based sensor management with mobile sensors
- Results indicate that the negotiation-based strategy (the N-tracker) has advantages over a greedy one (the G-tracker).

Future work

- Incorporate system model into expected measurements
- Agent uncertainty about world state