

# Path Planning for Swarms by Combining Probabilistic Roadmaps and Potential Fields

**Alex Wallar**

School of Computer Science  
University of St Andrews  
St Andrews, Scotland

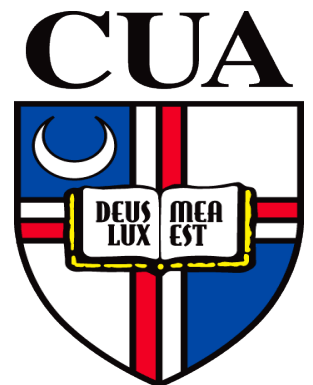
Erion Plaku

Dept. of Electrical Engineering  
and Computer Science  
Catholic University of America  
Washington DC, USA



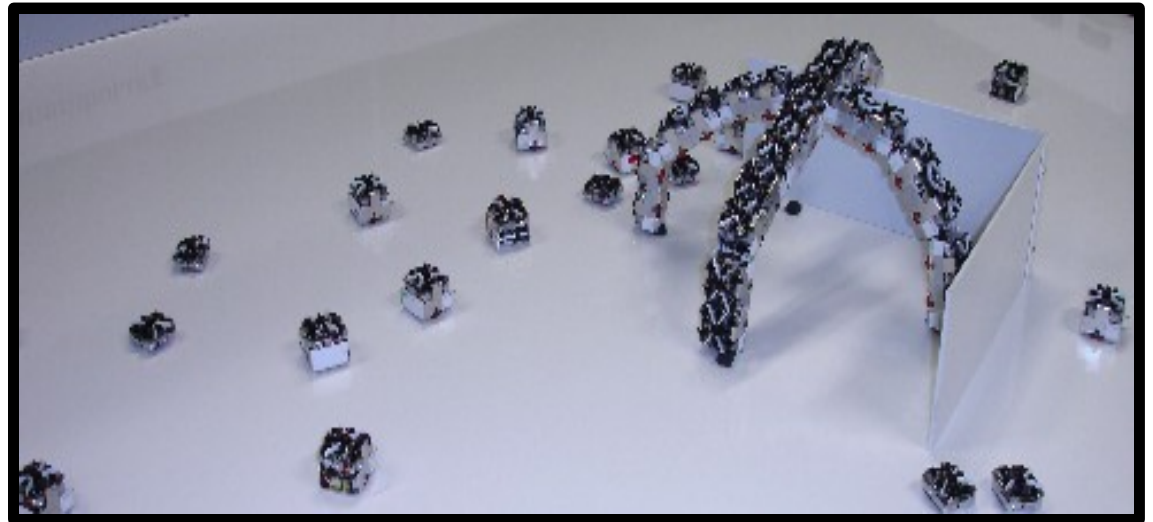
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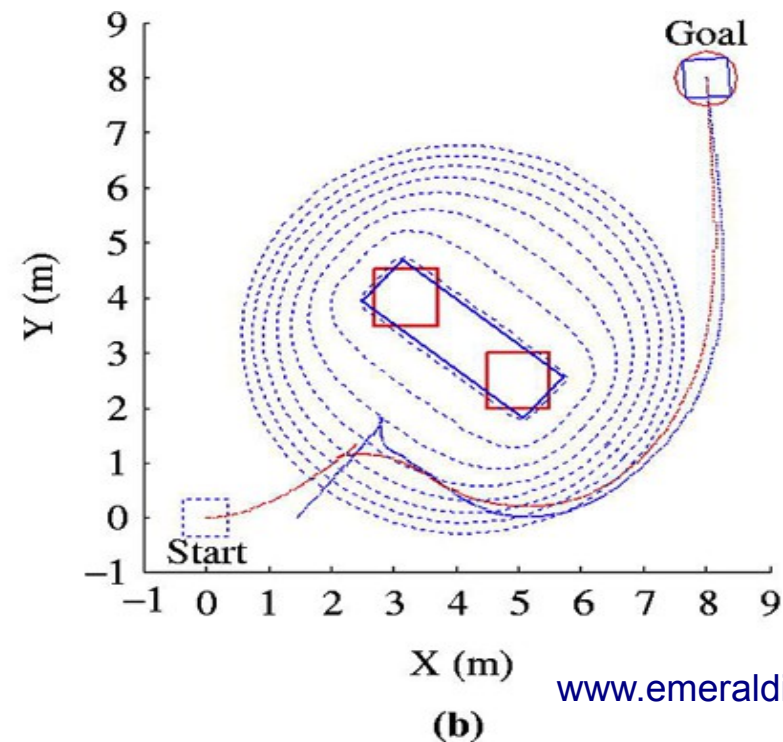
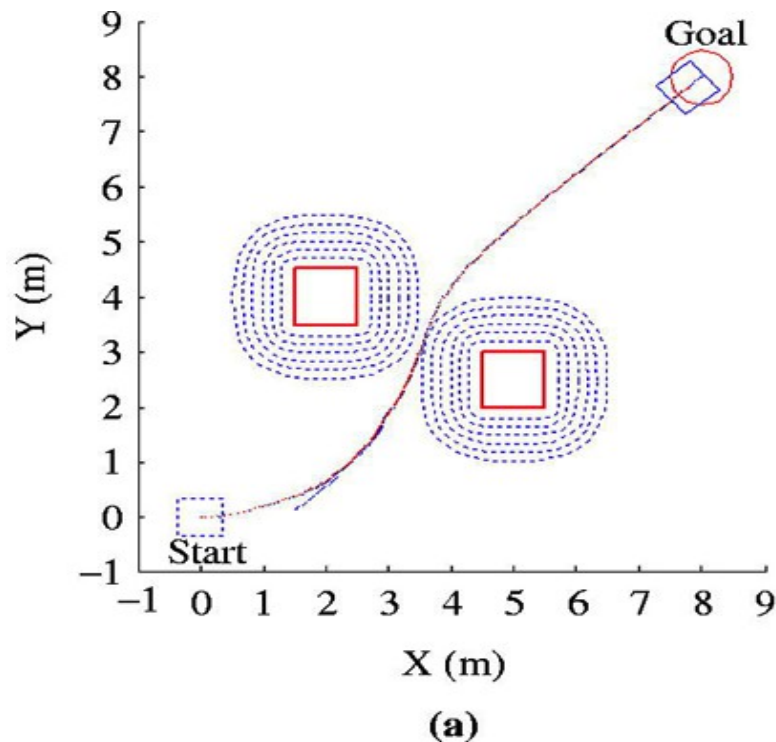
# Motivation

- Enables a large group of robots to complete complex tasks through simple interactions
- Used for
  - Monitoring
  - Mapping
  - Inspection
  - Surveying
  - Exploration
  - Search and Rescue



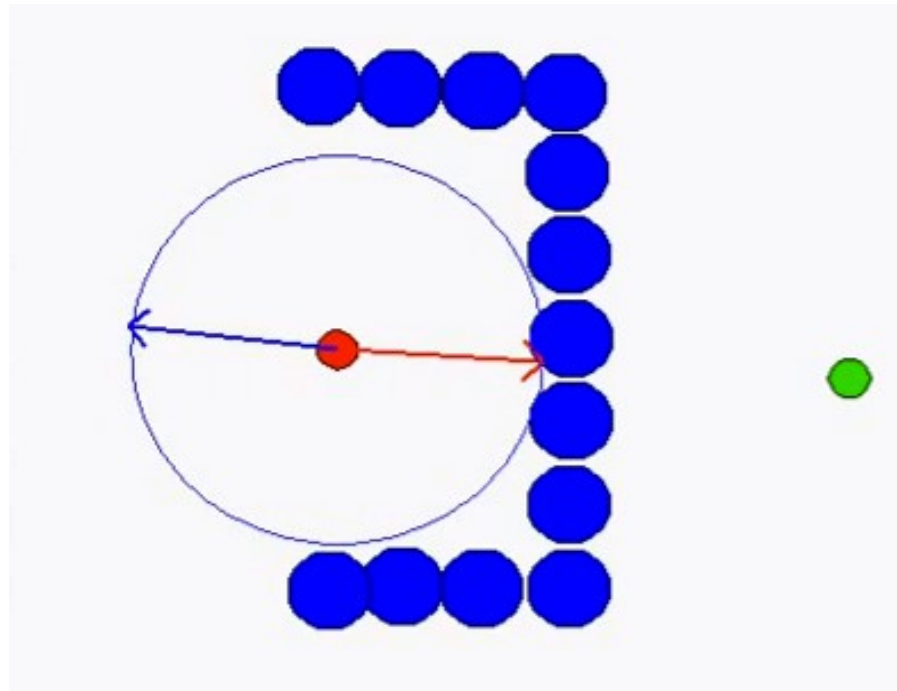
# Path Planning for Swarms via Potential Fields

- Attractive potential field around the goal
- Repulsive potential field around obstacles
- Very fast field computation



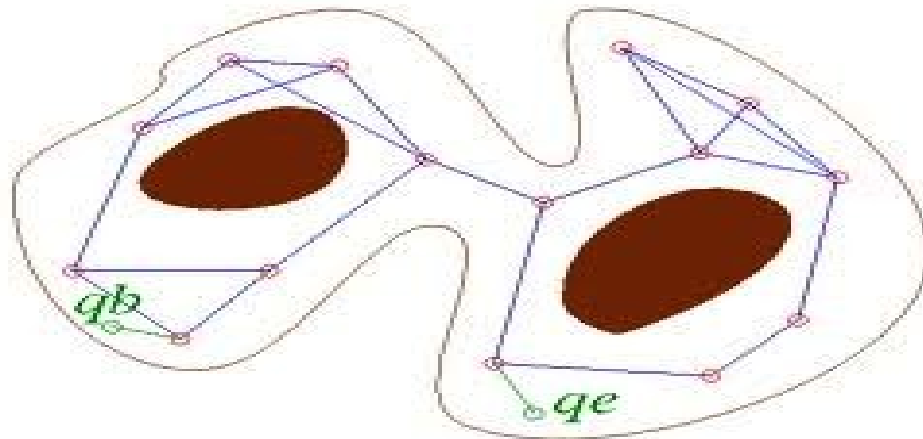
# Limitations of Path Planning via Potential Fields

- Local minima problem
- Potential fields often lead robots into local minima especially when dealing with complex environments and large swarms



# Path Planning for Swarms via Probabilistic Roadmaps (PRMs)

- Randomly distribute points in the environment
- Connect collision free points
- Use a shortest path algorithm to determine the path from initial to final configurations
- Captures the connectivity of the environment



# Limitations of Path Planning via PRMs

- As the number of robots increases
  - It becomes difficult to sample collision-free configurations
  - It becomes difficult to generate collision free paths
  - Larger roadmaps are needed to capture the connectivity of the sample space
- PRMs do not promote fluidity in movement

# Proposed Approach

- Combine roadmaps and potentials for swarms (CRoPS) to enable fast path planning for swarms
- Potential fields provide scalability
- Probabilistic roadmaps provide high-level guidance of how swarm should move towards the goal
- Bots will move in cohesion due to potential fields

# Swarm Motion

- There is long range attraction to intermediate goals and final destination
- Robots are repulsed from obstacles
- Robots move as a swarm while keeping some separation from one another
- A robot's heading is influenced by the headings of its neighbors

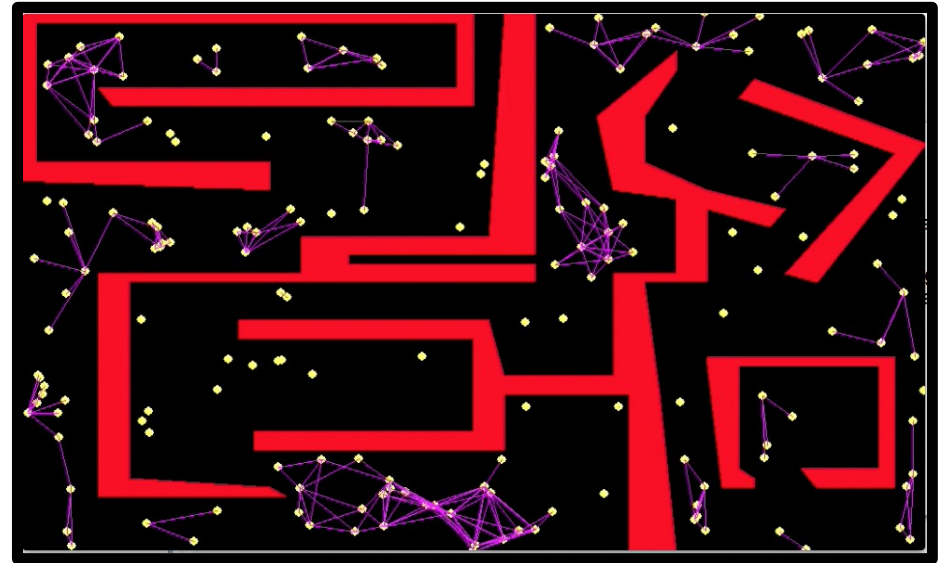


# CRoPS: Combined Roadmaps and Potential Fields

- Construct roadmap using PRM
- Search roadmap to compute intermediate goals for each the swarm
- Repeat until solved
  - assign next goal to boids that have reached current goal
  - compute overall potential for each boid
  - compute new heading based on overall potential
  - update positions

# Roadmap Construction

- Nodes are randomly distributed in environment
- Nodes are connected to  $k$  collision free nodes within a radius
- Nodes that spawn within a minimum distance from an obstacle are discarded



# Roadmap Weights

- In order to bias the swarm towards less cluttered areas, nodes further away from obstacles are assigned higher weights

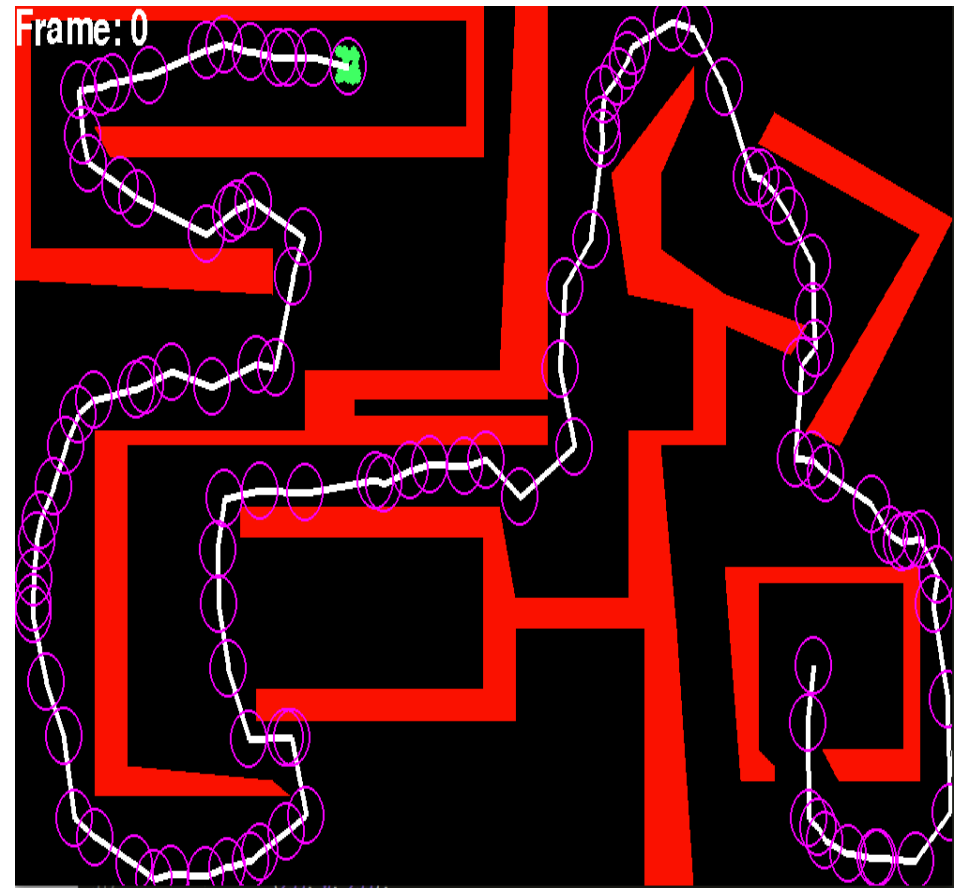
$$w(q_i) = \left( \sum_{o \in \text{Obstacles}} \text{dist}(q_i, o) \right)^3$$

- Edge costs reflect not only the distance among the endpoints, but also their clearance away from obstacles, i.e.,

$$w(q_i, q_j) = \|q_i, q_j\|_2 / \min(w(q_i), w(q_j))$$

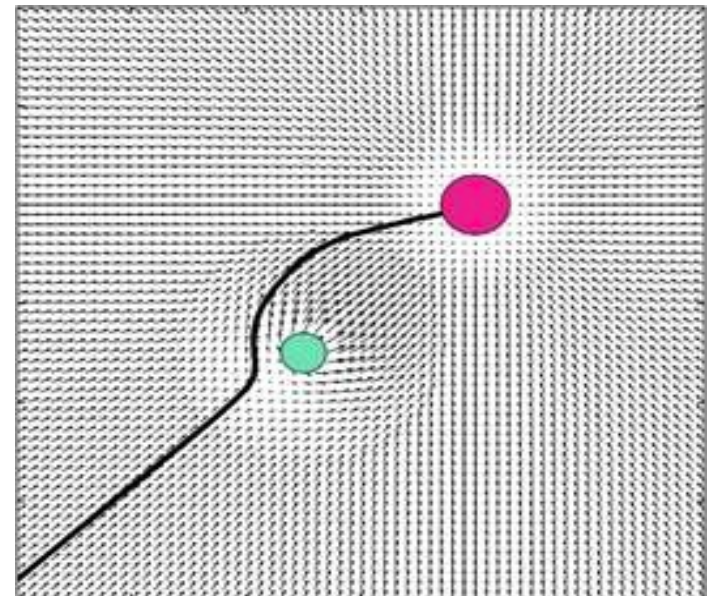
# Guiding the Swarm through the Shortest Roadmap Path

- Shortest roadmap path serves as high-level guide
- Computed using Dijkstra's algorithm
- Guide provides a series of intermediate goals defined as circles centered at the path vertices
- CRoPS seeks to move the swarm to the final destination by passing each bot through these intermediate goals



# Potential Fields

- **CRoPS** uses five potential fields
  - Repulsion from obstacles
  - Repulsion from other robots
  - Attraction to current intermediate goal
  - Neighbor heading influence
  - Random walks



# Repulsion From Obstacles

- A strong potential field is used to repel bots in the swarm from obstacles

$$P_{obst}(b, o) = \frac{1}{(\text{dist}(\text{pos}(b), o) - \text{radius}(b))^2}$$

- The repulsion is only computed for obstacles within a certain distance from the bot

$$PF_{obst}(b) = \sum_{\substack{o \in \text{Obstacles} \\ \text{dist}(b, o) \leq \Delta_{obst}}} (\text{pos}(b) - \text{ClosestPoint}(o, \text{pos}(b))) P_{obst}(b, o)$$

# Repulsion From Other Robots

- Robots should not come too close or too far from each other
- Uses weak sigmoidal potential function to show that obstacle field is dominant

$$P_{sep}(b_i, b_j) = \frac{1}{1 + \exp(\delta_{sep} ||\text{pos}(b_i), \text{pos}(b_j)||_2)}$$

- Similar to the obstacles, robots that are far away should not influence this field.

$$PF_{sep}(b) = \sum_{\substack{b_i \in \text{Robots} - \{b\} \\ \text{dist}(b, b_i) \leq \Delta_{sep}}} (\text{pos}(b) - \text{pos}(b_i)) P_{sep}(b, b_i)$$



# Attraction to Immediate Goal

- $igoal(b)$  represents the next immediate goal defined in the a shortest path for a boid  $b$ .
- A weak sigmoidal function is used to increase potential as the robot gets closer to the goal
- This allows the swarm to increase speed and promotes fluidity

$$PF_{igoal}(b) = \frac{igoal(b) - pos(b)}{1 + \exp(\delta_{igoal} ||pos(b), igoal(b)||_2)}$$

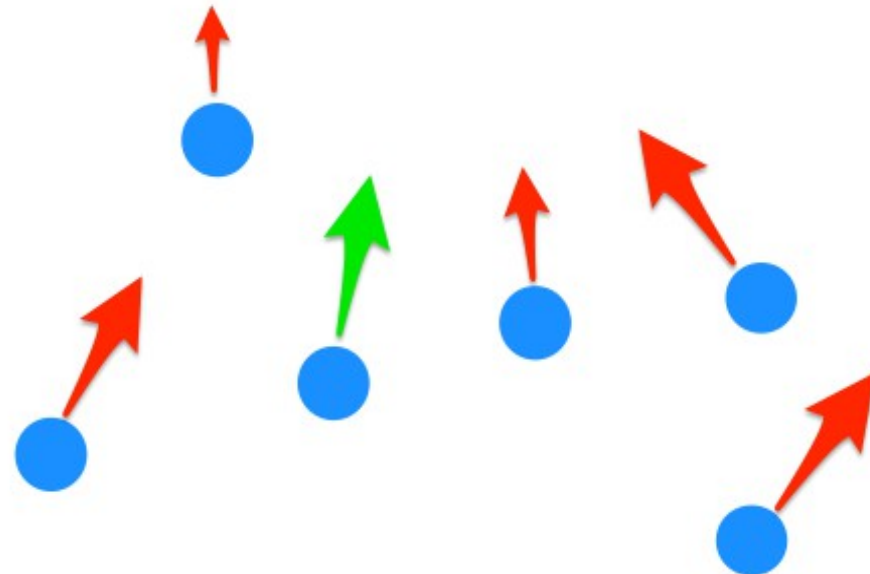


# Neighbor Heading Influence

- The heading of a robot is influenced by the headings of its neighbors
- The neighbors are chosen to be not too far nor too close
- Moreover, bots that are “stuck” are unable to be chosen

$$\gamma(b, b_i) = \exp \left( \frac{-(\|pos(b), pos(b_i)\|_2 - \mu)^2}{2\sigma^2} \right)$$

$$PF_{heading}(b) = \sum_{b_i \in Neighs(b)} heading(b_i)$$



# Escaping Local Minima

- Each robot keeps track of past its past locations
- Bot is considered stuck if it has moved very little in the last  $l$  time steps

$$stuck(b) = \begin{cases} 1, & \text{if } ||pos(b) - prev_{\ell}(b)||_2 < \Delta_{stuck} \\ 0, & \text{otherwise,} \end{cases}$$

- If the bot is stuck, a random walk in the form of another potential field is applied

$$PF_{escape}(b) = stuck(b)(r_x, r_y)$$

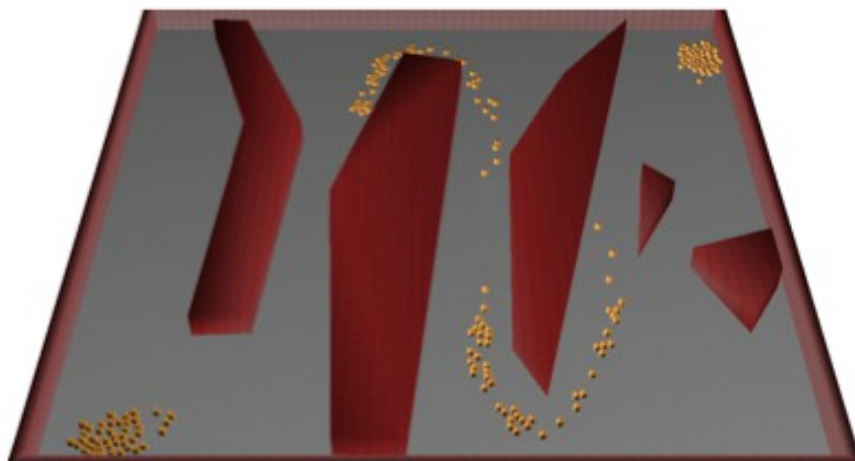
# Superimposition of Potential Fields

- Different potential fields are superimposed to obtain the overall force vector applied to the robot
- This superimposition ensures that the subfield with the highest potential has the most influence

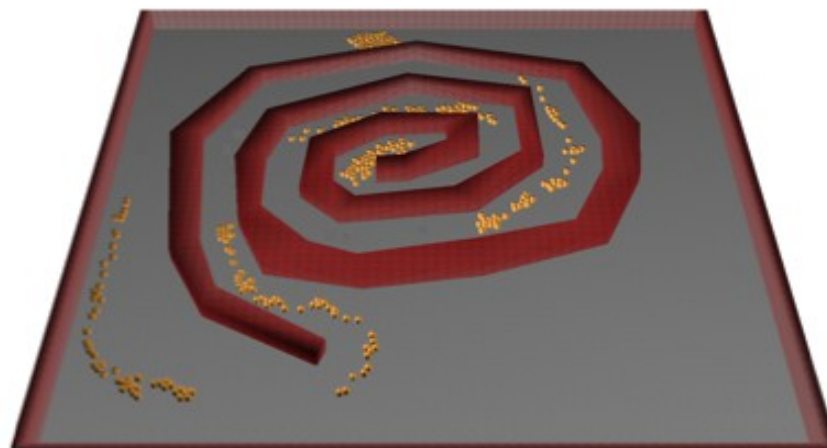
$$PF(b) = \frac{\sum_{\phi \in fields} (\|PF_{\phi}(b)\|_2 PF_{\phi}(b))}{\sum_{\phi \in fields} \|PF_{\phi}(b)\|_2}$$

$$fields = \{obst, sep, igoal, heading, escape\}$$

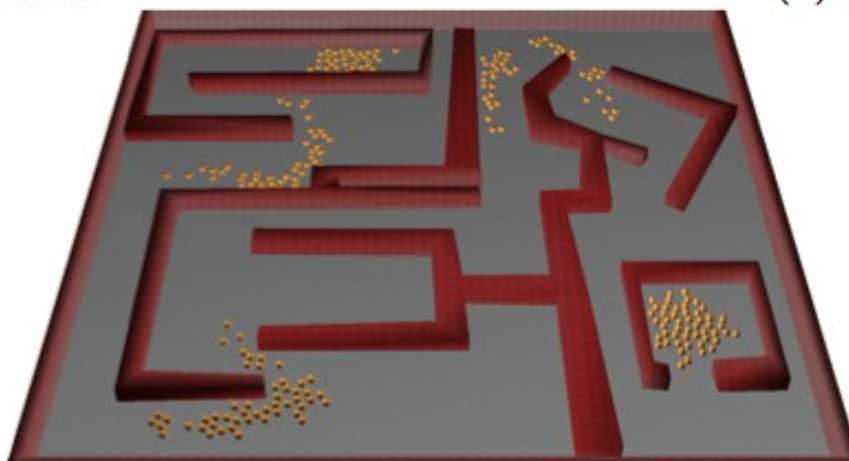
# Experiments and Results



(a) scene1



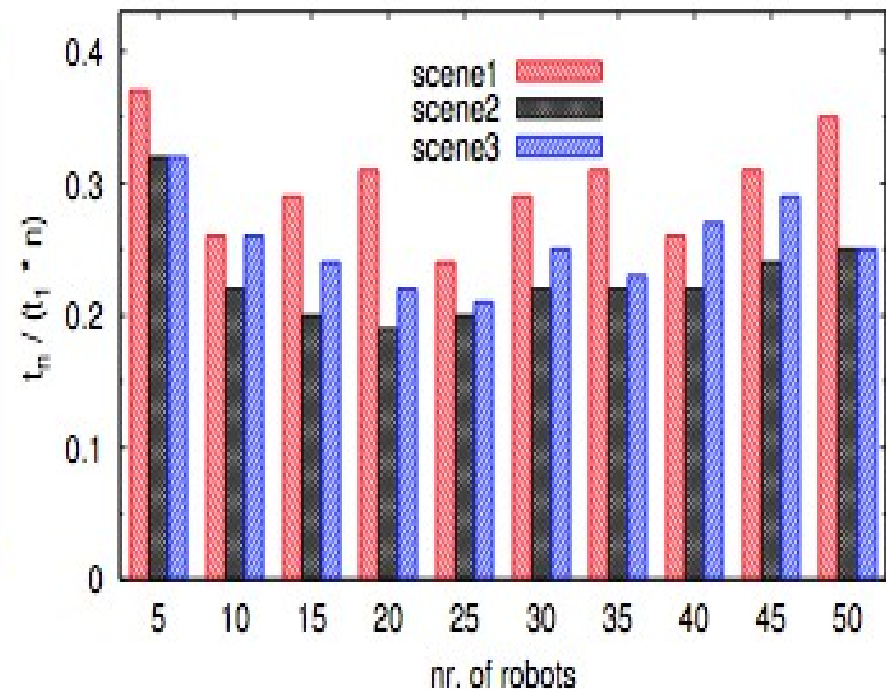
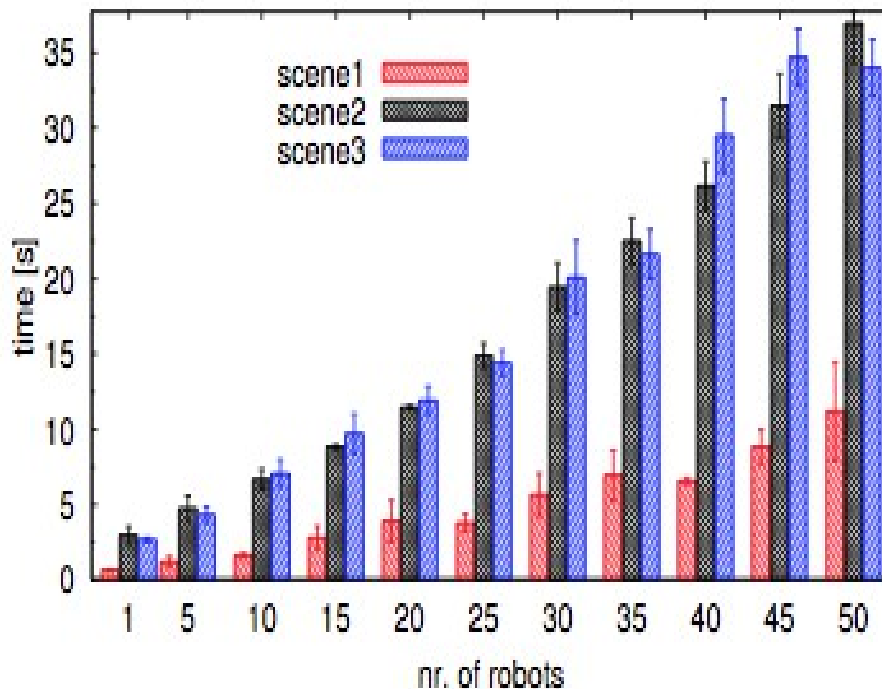
(b) scene2



(c) scene3

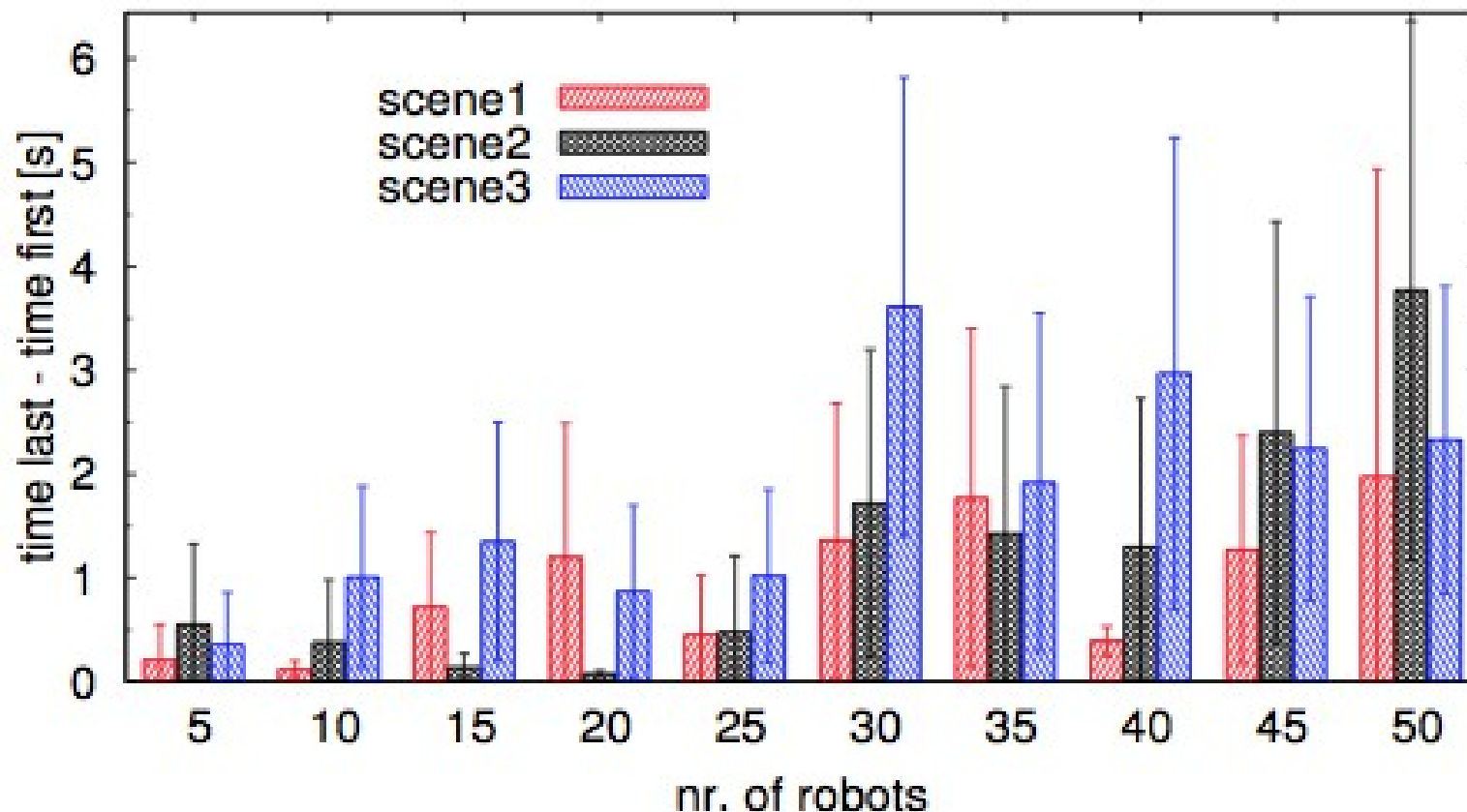
# Time Analysis

- Graph 1 & 2 show that as the number of robots increase, the time needed to navigate through each environment increases linearly



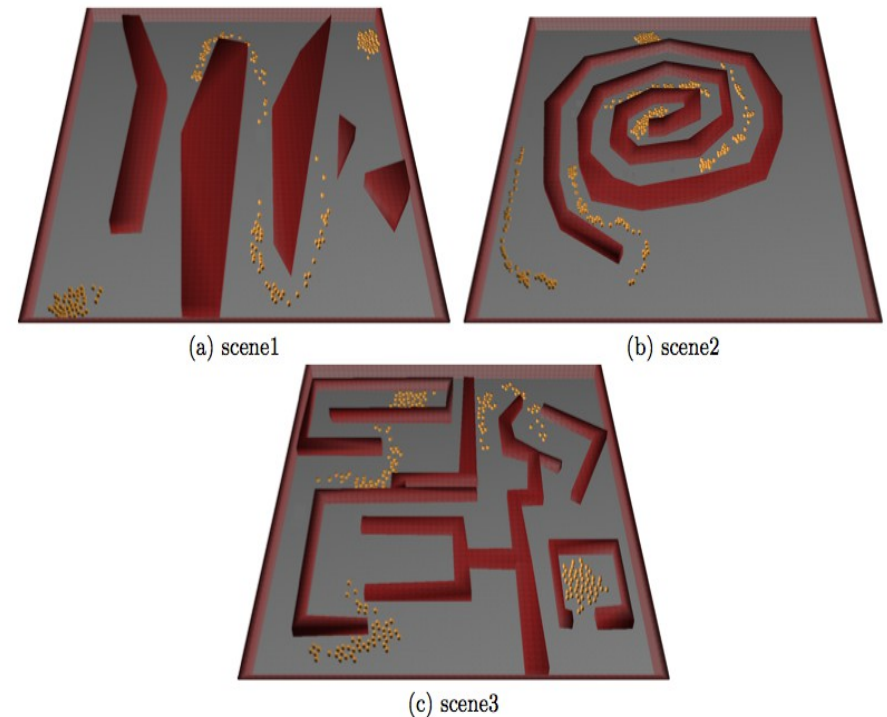
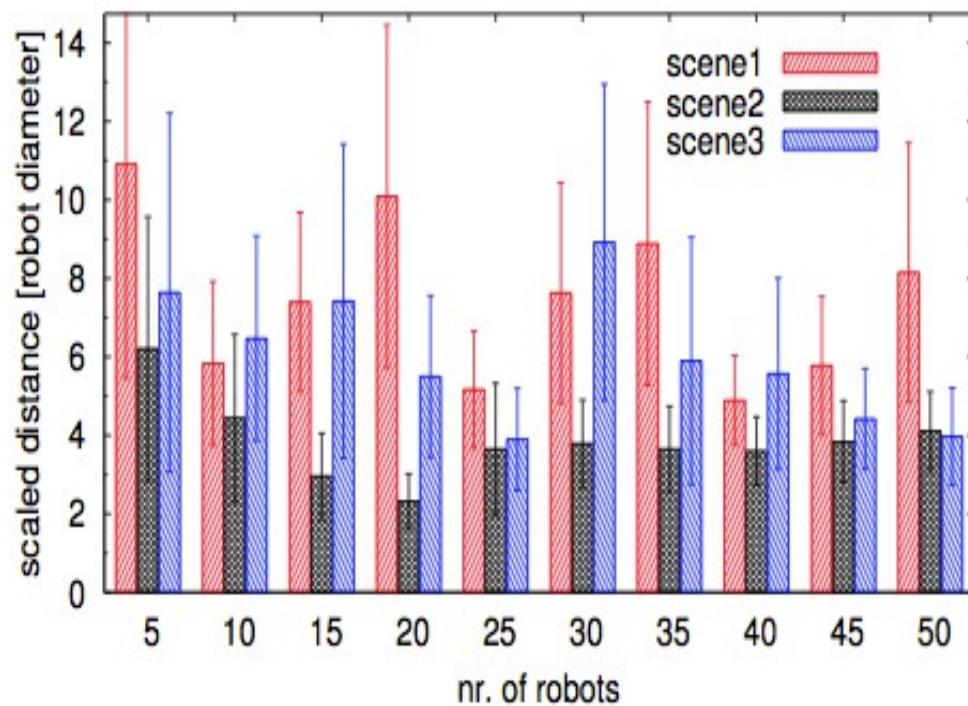
# Swarm Analysis 1

- Figure shows that robots reach the last goal at generally the same time on different environments



# Swarm Analysis 2

- Varied levels of separation based on the environment
- Separation generally constant regardless of number of bots



# Research Direction

- Incorporate moving obstacles
- Improve the interplay between the global path planner and the potential fields
- Deal with probabilistic environments
- Create threat maps based on amount of movements in an area
- Increase the dimensions of the environment



# Conclusion

- The combination between potential fields and low dimensional roadmaps enable fast swarm planning
- **CRoPS** presents an efficient, computationally cheap algorithm for swarm path planning
- **CRoPS** is scalable due to the linear time complexity
- Bots still act as a swarm, obeying the four base principles

# Questions

