University at Buffalo *The State University of New York*

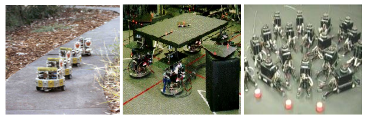
Decentralized Motion Planning for Cooperative Payload Transport by Robot Collectives

Research Goal:

Evaluate alternative decentralized motion planning schemes for cooperative payload transport by robot collectives within a potential field framework.

Motivations:

Group behavior in nature - fish, birds, & ants.



Example of cooperative robot Systems.

- Task might be inherently too complex for a single robot to accomplish.
- Significant overall performance can be achieved by using a group of robots.
- Constructing and delivering of simple small-sized robots can be easier, cheaper and more flexible and more fault tolerance.
- The constructive, synthetic approach inherent in the in cooperative robots can possible yield insights to the social science (organizational theory, cognitive psychology) and life sciences (theoretical biology, animal anthology).

Challenges :

- Perform motion planning for a group of robots to a specific target while ***avoiding obstacles***.
- For payload transport, ***formation maintenance*** during the course of motion is crucial.

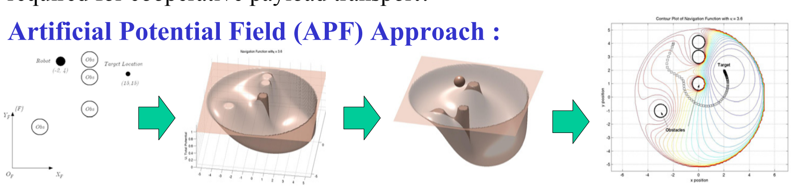
Our Approaches:

- Obstacle avoidance problem is handled using ***Potential Field Approach***.
- Formation maintaining problem is solve by formulation the cooperative system as a ***constrained mechanical system.***

Specific Research Questions:

- Which potential function is suitable for motion planning for group of robot?
- How can we extend the potential framework to help maintain formation?
- How can we further extend this framework to realize the tight formation contact required for cooperative payload transport?

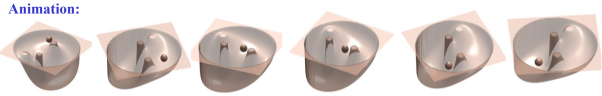
Artificial Potential Field (APF) Approach :



Workspace and Robot. Workspace Modeled using APF. Model the robots as a marble. Simulation showing path of robot.

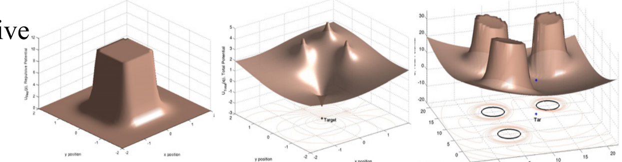
IDEA: Model the robots as a marble and motion planning become letting the marbles rolling downward in the potential field and reach the target while avoiding obstacle.

Animation:



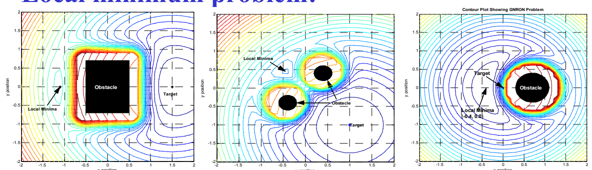
t = 0 sec t = 2 sec t = 4 sec t = 6 sec t = 8 sec t = 10 sec

Finding the suitable potential function:



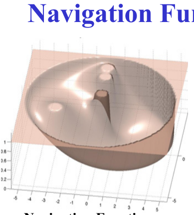
FIRAS Function Harmonic Function Ge New Potential

Local minimum problem:



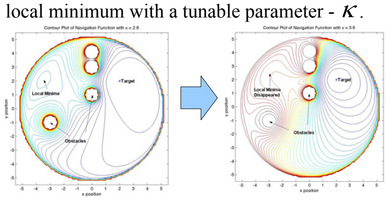
Result from single obstacle Result of multiple obstacles Target too close to obstacle

Navigation Function:



Navigation Function

A potential function that guaranteed a unique local minimum with a tunable parameter - κ.



Dynamic Formulation for Group of Robots:

$$\dot{\mathbf{q}} = \mathbf{v}$$

$$\mathbf{M}(\mathbf{q})\dot{\mathbf{v}} = \mathbf{f}(\mathbf{q},\mathbf{v},t,\mathbf{u}) - \mathbf{J}(\mathbf{q})^T \boldsymbol{\lambda}$$

$$\mathbf{C}(\mathbf{q},t) = \mathbf{0}$$

$\mathbf{q}$ is the *n*-dimensional vector of generalized coordinates

$\mathbf{v}$ is the *n*-dimensional vector of generalized velocities

$\mathbf{M}(\mathbf{q})$ is the *n*-dimensional vector of generalized velocities

$\mathbf{f}(\mathbf{q},\mathbf{v},t,\mathbf{u})$ is the *n*-dimensional vector of external forces

$\mathbf{u}$ is the vector of input forces, which is $-\mathbf{k}_f \nabla_q U$

$\mathbf{J}(\mathbf{q}) = \frac{\partial \mathbf{C}(\mathbf{q})}{\partial \mathbf{q}}$ is the *Jacobian* matrix

The Lagrange Equation can be solved using:

Method I: Direct Lagrange Multiplier Elimination Approach

- *Explicitly computing the Lagrange multiplier by a projection into the constrained force space*

Method II: Penalty Formulation Approach

- *Approximating the Lagrange multiplier using artificial compliance elements such as virtual springs and dampers*

Method III: Constraints Manifold Projection Based Approach

- *By projecting the equations of motion onto the tangent space of the constraint manifold in a variety of ways to obtain constraint-reaction free equations of motions*

Case Study – Group of three point-mass robots:

A group of three point-mass robots forming a triangular shape served as our model for the case studies.

Equation of motion:

$$\dot{\mathbf{q}} = \mathbf{v}$$

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{V}(\mathbf{q},\dot{\mathbf{q}}) + \mathbf{G}(\mathbf{q}) = \mathbf{E}(\mathbf{q})\mathbf{u} - \mathbf{J}^T\boldsymbol{\lambda}$$

$$\mathbf{J}(\mathbf{q})\dot{\mathbf{q}} + \sigma\mathbf{C}(\mathbf{q}) = \mathbf{0}$$

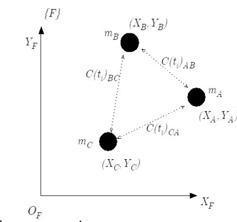
Formation Error is obtained by:

$$\Delta_{Error} = \sqrt{(c_{AB} - \bar{c}_{AB})^2 + (c_{BC} - \bar{c}_{BC})^2 + (c_{CA} - \bar{c}_{CA})^2}$$

Δ_{Error} is the total formation error;

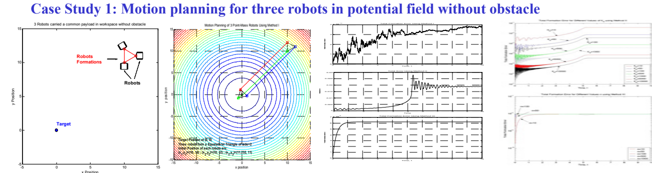
c_{ij} is the actual Euclidean distance between robot i and robot j

$\bar{c}_{ij}$ is the desired Euclidean distance between robot i and robot j



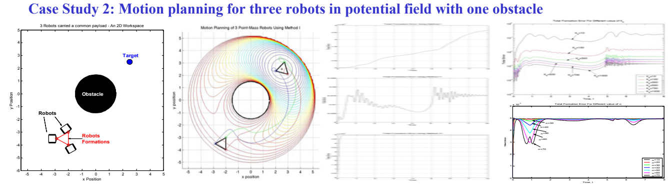
Results:

Case Study 1: Motion planning for three robots in potential field without obstacle



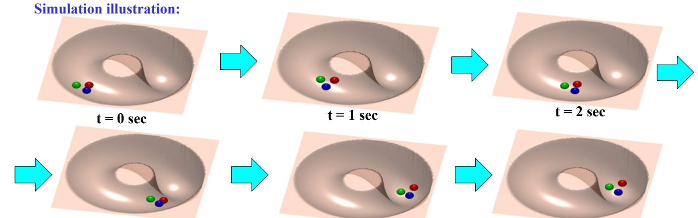
Setup for case study 1 Simulation result Error of each method Parameter study

Case Study 2: Motion planning for three robots in potential field with one obstacle



Setup for case study 1 Simulation result Error of each method Parameter study

Simulation illustration:



t = 0 sec t = 1 sec t = 2 sec t = 4 sec t = 6 sec t = 8 sec

Conclusion:

We obtained the following general characteristics for the three methods from the case studies:

Formation Accuracy: *Method III > Method I > Method II*

Computation Efficiency: *Method I > Method II > Method III*

Decentralized Formulation Ability: *Method I Method III Method II*

Centralized → Decentralized

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