Collaborative Control of Moving Agents Under Communication and Functionality Constraints

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Control with Communication Constraints

- Control problems where **information used for feedback needs to be transmitted across communication channels** with rate constraints:
  - Explicit data compression
  - Bits associated with key features of the on-line measurements
  - Adaptive modulation to "squeeze" more data through the channel
  - Adaptive error coding for variable quality channels ("booster" protocols)
- Data compression, modulation and coding (CMC) schemes **are themselves decision variables and should be optimized**
- **Design jointly the communication and control scheme** in a way that asynchronous and distributed operation results in acceptable performance

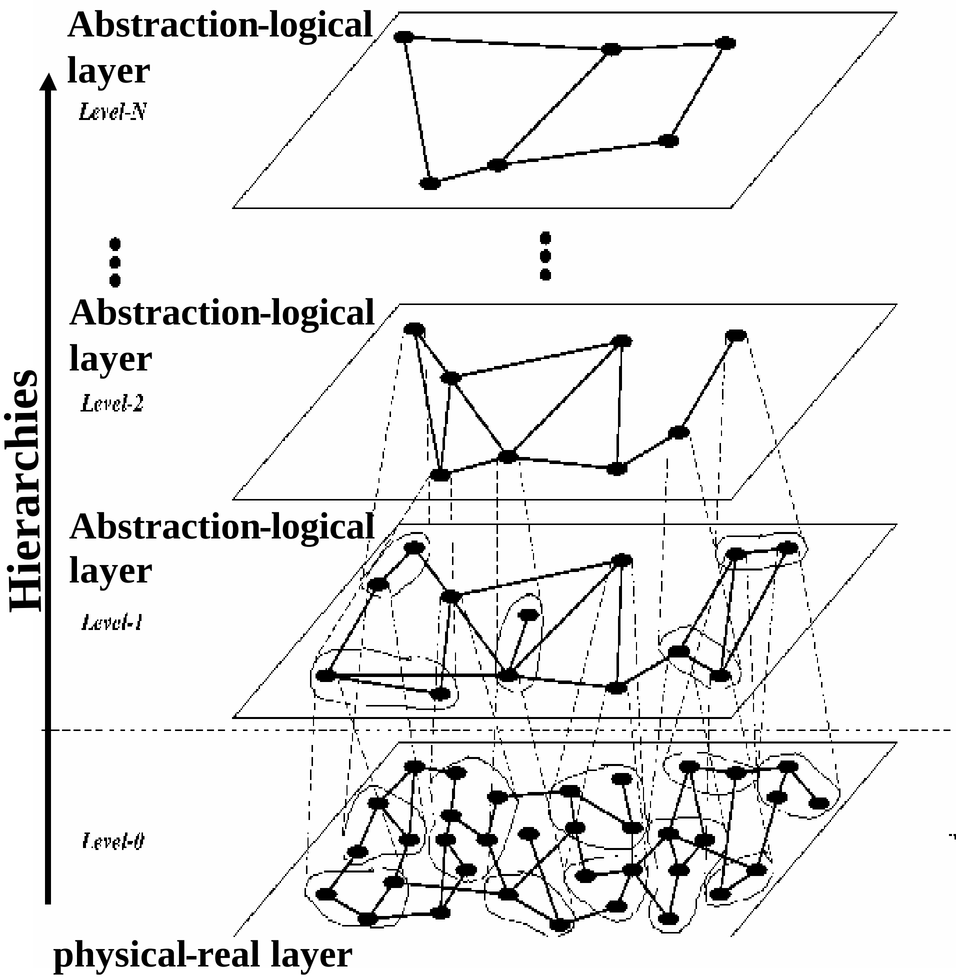
Intelligent Control of Communicating Networked Control Systems

- **Distributed and asynchronous schemes pose foundational challenges (e.g. local states, multiple threads)**
- **Architecture/organization**
- **Framework aims to link together in a trade-off analysis**
  - the performance quality of the control systems
  - the communication constraints and the quality of the communications
  - the inherent uncertainty of these systems (architecture, models, data)
  - the computational complexity (especially under asynchronous and distributed operations)
- **Learning is an important component (reinforcement learning)**
- **Need for implementable solutions**

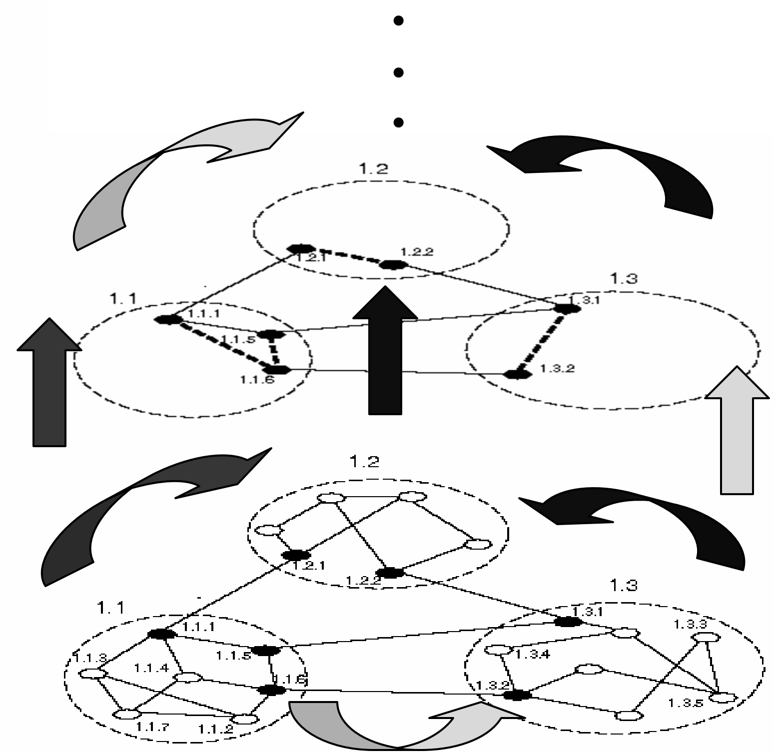
Organization via Aggregations

- Central idea: need to "organize" the network of communicating control systems in some systematic way, to achieve efficiency in communication without sacrificing much performance
- Leads to performance driven aggregation: either in the physical layer or in the abstractions and models used by the control schemes
- We investigated aggregation/approximation via state aggregation
- We developed learning algorithms with state aggregation
- Distributed and asynchronous (partially) such schemes are needed
- Aggregations lead naturally to communicating architectures, in addition to establishing trade-offs between control performance and communication resources needed to achieve it
- Steps of our methodology lead to the design of self-organization schemes for the intelligent control of networked control systems

Value Level Sets / Aggregation / Organization



Local-Global exchanges:
estimates of value functions
other parameters
topology configuration



Jointly Optimal Quantization, Estimation, and Control of Hidden Markov Chains

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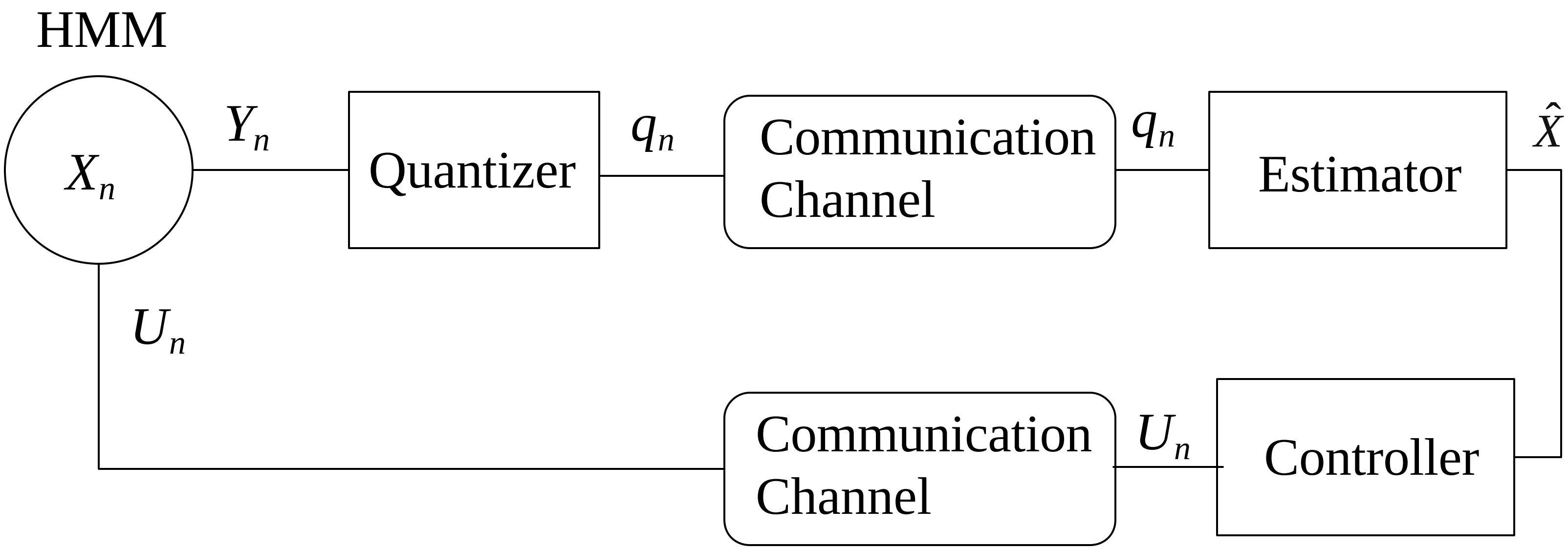
Outline

- Goal
  - To explore a general framework for trade-off analysis and decision making in networked control systems
- Joint quantization and estimation
- Joint quantization and control
- Conclusions



The setup for joint quantization, estimation, and control of an HMM.

Joint Quantization and Estimation

Vector quantization with variable block length is considered.
The total cost to be minimized is a weighted sum of three terms:

$$J(\Pi_0, w) = E[\sum_{n=1}^{N} J^q(n) + l_d J^d(n) + l_e J^e(n)],$$

where ? $_0$ is the *a priori* PMF for X_0, and ? is the quantization decision.

- $J^q(n)$: Communication cost at time n. Entropy coding is assumed.
- $J^d(n)$: Delay cost (due to block coding) evaluated at time n.
- $J^e(n)$: Estimation error for X_n.

The value function:

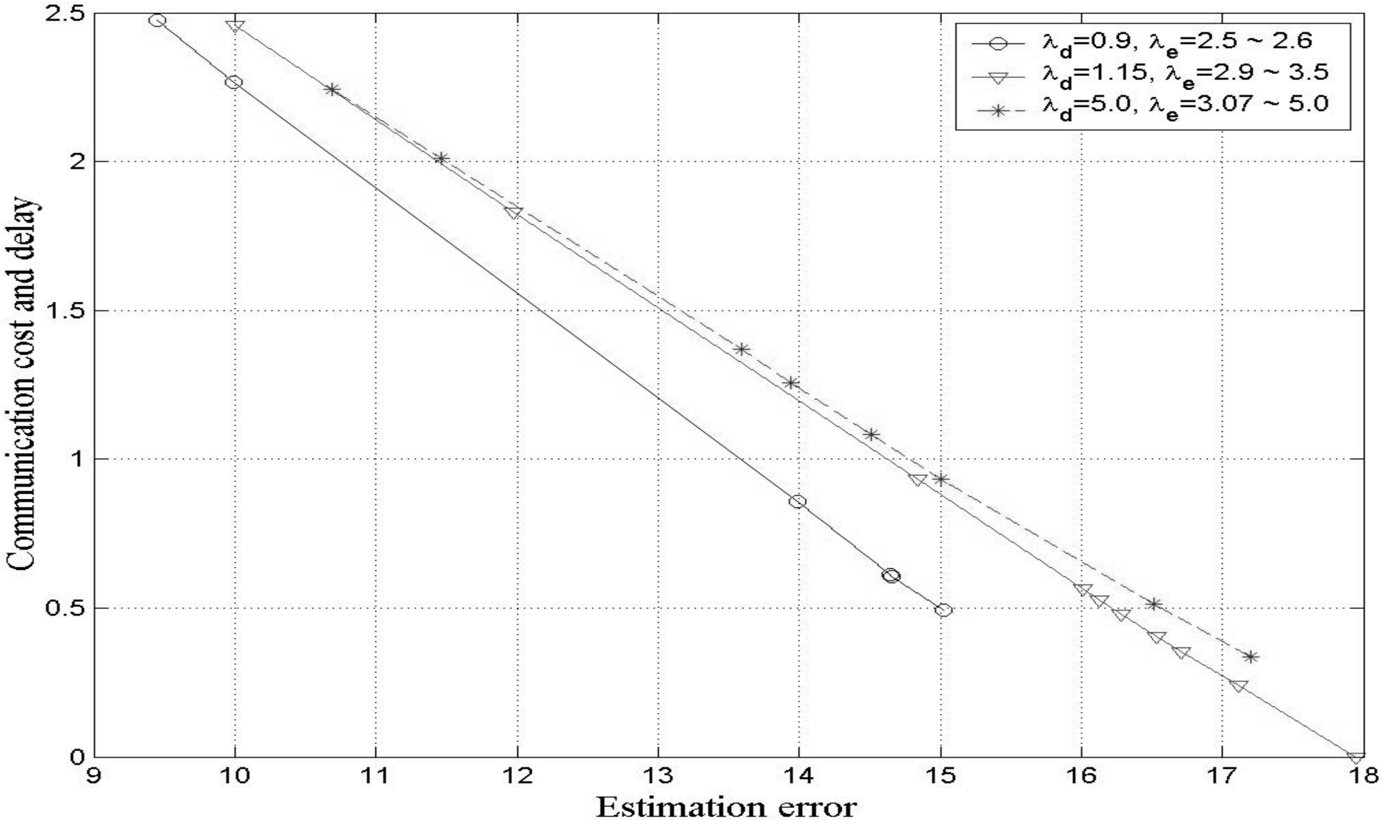
$$V(\Pi_0) = \min_w J(\Pi_0, w).$$

Numerical Solution of the Dynamic Programming Equation

- The separation principle holds, and the value function satisfies a special type of dynamic programming equation
- Enumeration and comparison of all partition (encoding) schemes are required in numerically solving the DP.
  - A tree-structured algorithm is developed to find all the *partition patterns*
  - *"characteristic numbers"* of partitions are used to eliminate redundant partitions

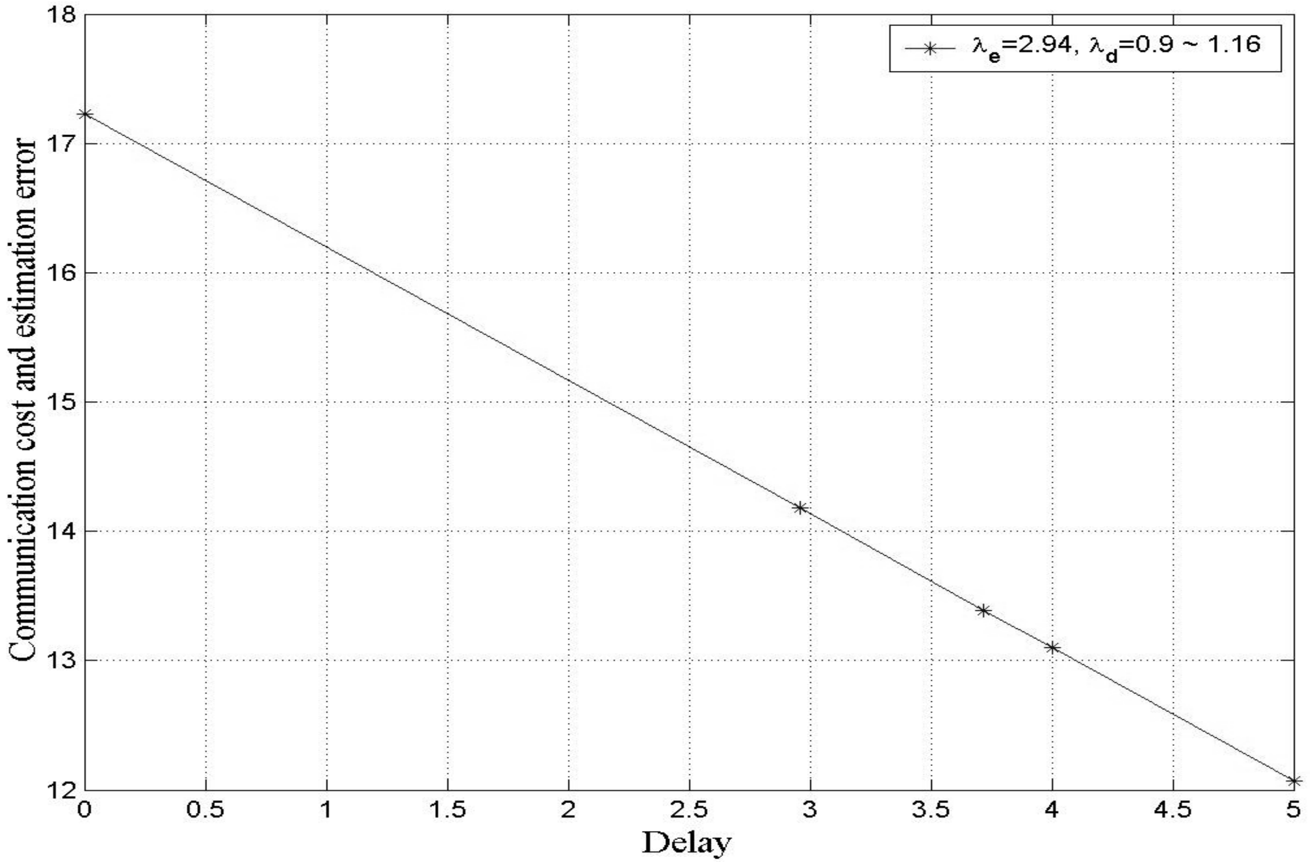
Numerical Results

Two states, two outputs, maximum block length=2.



Weighted combination of communication cost *vs.* estimation error (points with lower estimation error corresponding to higher ?$_e$);

Numerical Results (continued)



Weighted combination of communication cost and estimation error *vs.* delay (points with smaller delay corresponding to higher ?$_d$).

Joint Quantization and Control

The total cost to be minimized is a weighted sum of two terms:

$$J(\Pi_0, x) = E[\sum_{n=1}^{N} l_q J^q(n) + J^p(n)],$$

where ? $_0$ is the *a priori* PMF for X_0, and *?* is the quantization/control decision.

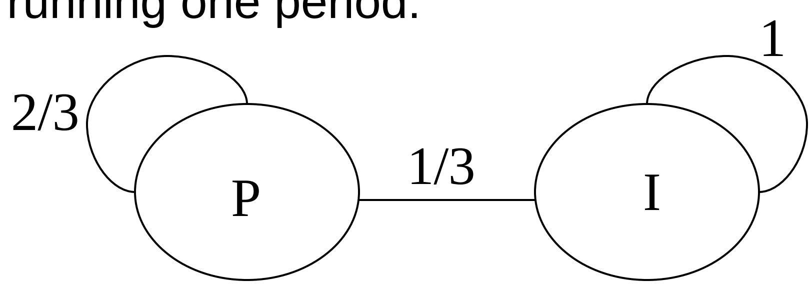
- $J^q(n)$: Communication cost at time n. Sequential (but time-varying) quantization is considered.
- $J^p(n)$: Cost related to control performance at time n, in general a function of state and control.

Separation principle also holds. The jointly optimal scheme can be obtained through solving a dynamic programming equation.

An Example Problem

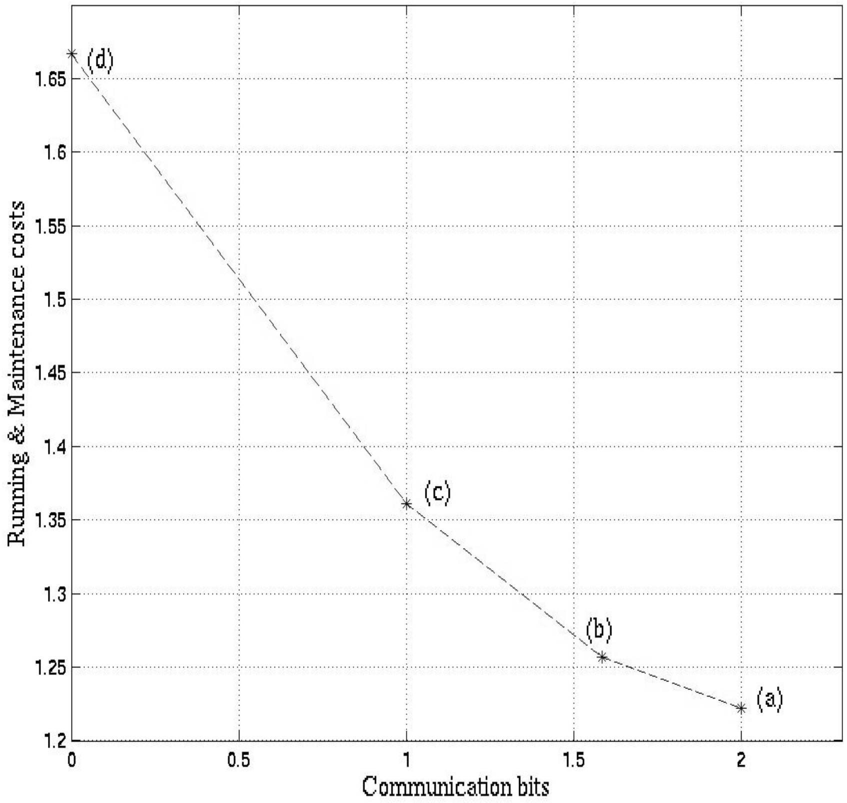
- A machine can be in two states: P (proper) or I (improper)
- An inspection produces one of two possible outcomes: G (good) or B (bad) with the following prob.:

- The outcome can be sent to a remote site (with communication cost $?_q$ per bit) for decision;
- One of two actions are possible: R (run the machine for one period) or S (perform maintenance and run the machine). “S” resets the state to be “P” but costs 1 unit. Running machine in “I” costs 2, and running it in “P” costs 0.
- State transition after running one period:



An Example Problem (continued)

A two-stage problem is solved explicitly. One of four joint quantization and control strategies becomes optimal depending on $?_q$.



Running and maintenance cost *vs*. Communication bits for jointly optimal strategies (fewer communication bits corresponding to higher $?_q$).

The thresholds of for switching of the optimal strategy correspond to the negative slopes of the line segments.

Conclusions and Future Work

- A framework for joint quantization/estimation/control was studied for a hidden Markov chain
  - A weighted combination of different costs is minimized;
  - Separation principle holds, and the problem is solved through DP;
  - Tradeoffs among competing goals can be captured by adjusting the weights.
- “Curse of dimensionality” presents a hurdle when the number of states is large. Approximation methods need to be developed for solving the DP equations.
- Application of the approach to “steady-state” problems (or asymptotic limits) may yield interesting insights for general problems while waived from actually solving DP.

Decentralized Control of Autonomous Vehicles

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Overview

- Objective
  - To explore a decentralized approach for multi-vehicle control;
  - To study the collective behavior arising from local interactions.
- A battlefield scenario
- Path generation based on potential functions
- Analysis of vehicle behaviors
- Simulation results
- Conclusions and future work

A Battlefield Scenario

- Mission
  - To maneuver a group of vehicles to cover a target area.
- Constraints
  - Maintaining a desired inter-vehicle distance (for good area coverage and collision avoidance);
  - Avoiding obstacles;
  - Avoiding threats (stationary ones and moving ones);
- Requirement
  - Using only local information about neighbors/threats or static (global) information about obstacles/target.

Potential Functions

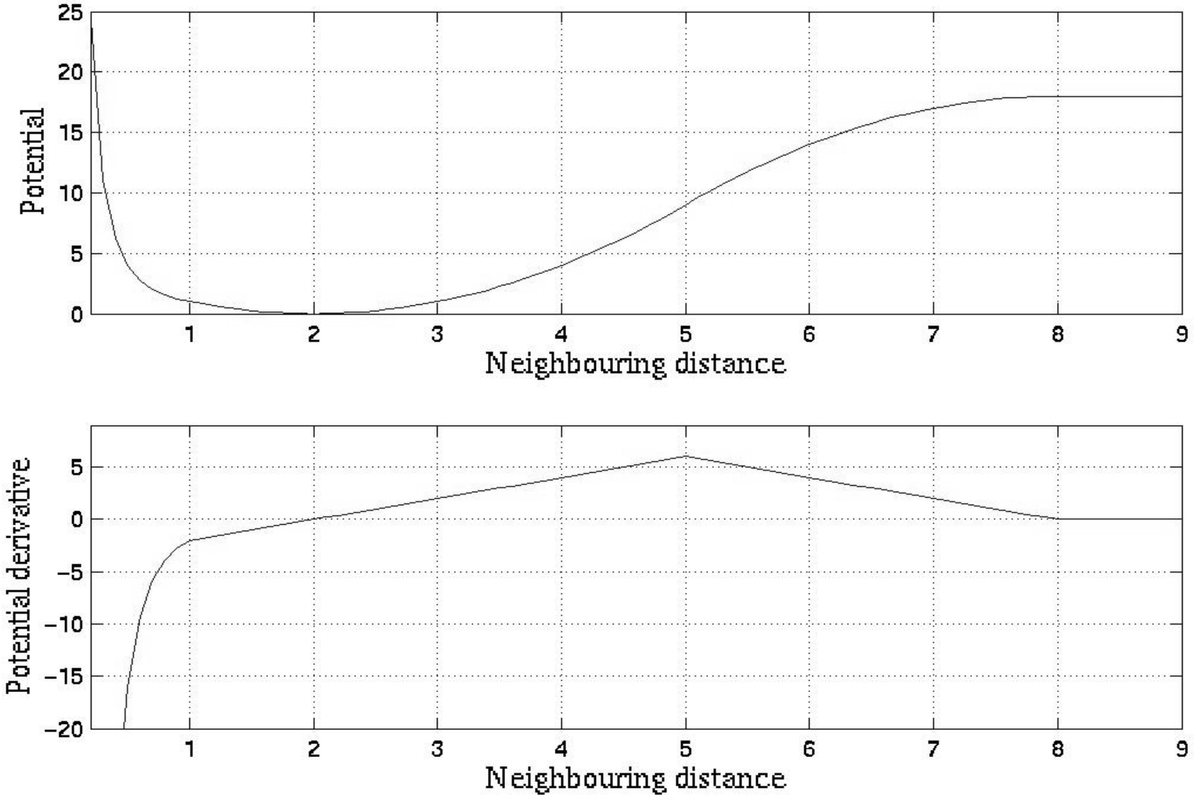
For the *i*-th vehicle with position q_i, its potential function at time t is:

$$J_{i,t}(q_i) = l_g J^g(q_i) + l_n J_{i,t}{}^n(q_i) + l_o J^o(q_i) + l_s J^s(q_i) + l_m J_t{}^m(q_i),$$

and the velocity is given by $\dot{q}_i(t) = -\dfrac{\partial J_{i,t}(q_i)}{\partial q_i}.$

- Target potential J^g
- Neighboring potential J^n
- Obstacle potential J^o
- Potential J^s due to stationary threats
- Potential J^m due to moving threats

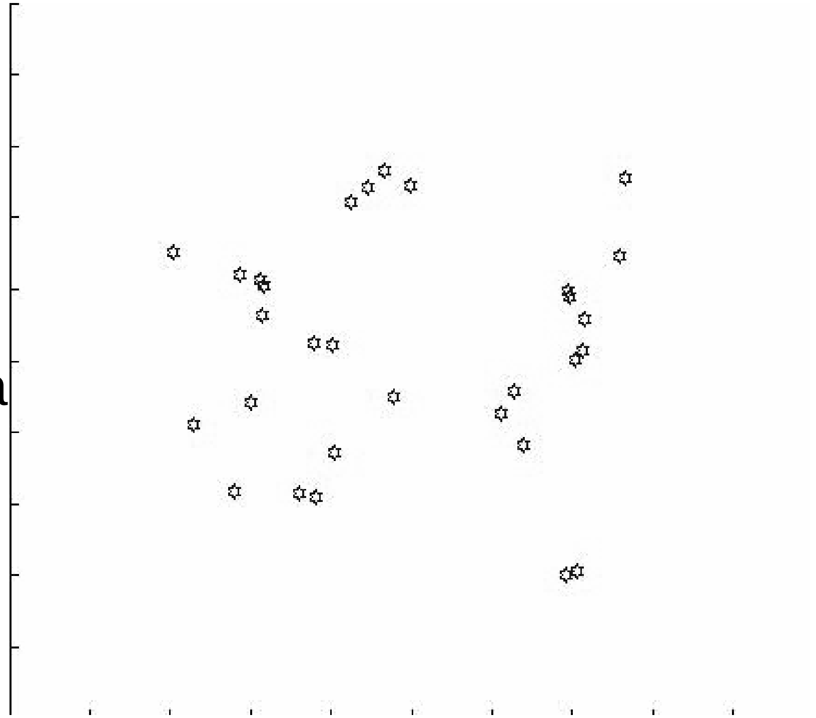
The neighboring potential and the moving threat potential are designed in such a way that they have no effect on the vehicle dynamics beyond the communication/detection range. This enables decentralized decision making.



An example of the neighboring potential function and its corresponding attractive/repulsive effect.

Equilibrium Formations under Inter-vehicle Interactions

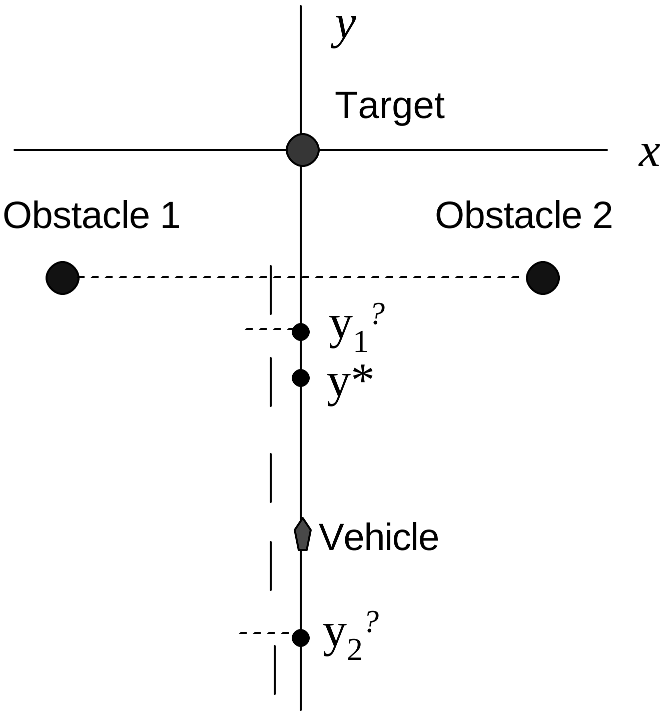
- For *N*=2, or 3, there is a unique asymptotically stable equilibrium, where the optimal inter-vehicle distance is achieved;
- For N>3, there may exist multiple locally asymptotically stable equilibria and the specific formation the group achieves depends on the initial condition;
- Extensive simulation appears to support that final formations are usually “well organized” under the purely local interactions.



Formation of 30 vehicles under local interactions starting from a random initialization.

Behavior under Attraction and Repulsion (I)

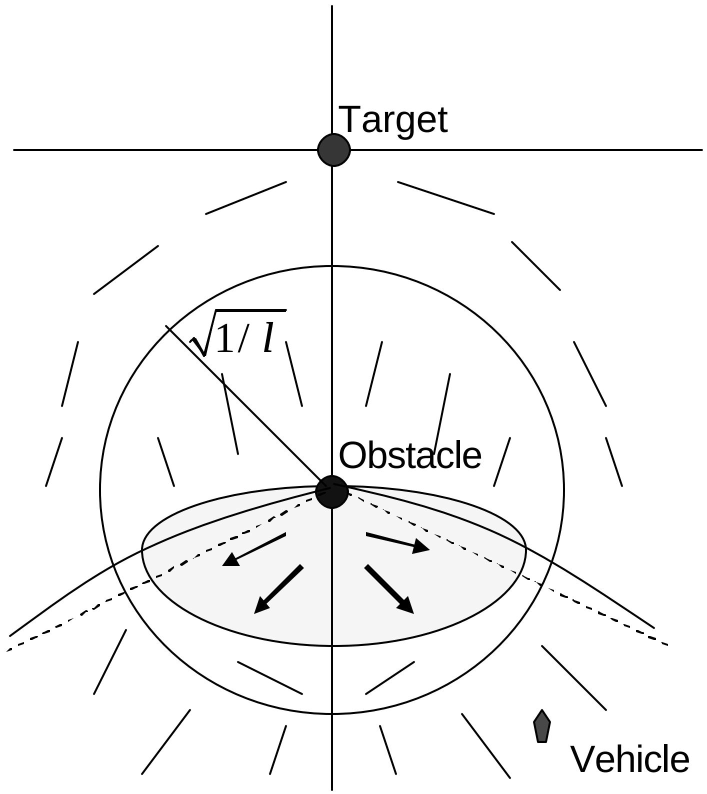
This is to study the behavior of a vehicle under both the attraction from a target and the repulsion from obstacles ($J = ?\, J^g + J^o$); in particular, how the behavior is affected by the weighting coefficient $?$.



Vector field on the y-axis.

- **Scenario I:** one target, two obstacles located symmetrically about the y-axis. A vehicle initially on y-axis.
- **Question:** can the vehicle pass the obstacle potential valley and get to the target?
- **Answer:** there exists $?^*$ such that
  - when $? > ?^*$, the vehicle can pass the valley;
  - when $? < ?^*$, there is $[y_2^{?}, y_1^{?}]$ dependent on $?$ where the vehicle is pushed away from the target. As $?$ approaches $?^*$, this interval collapses into a single point y^*.

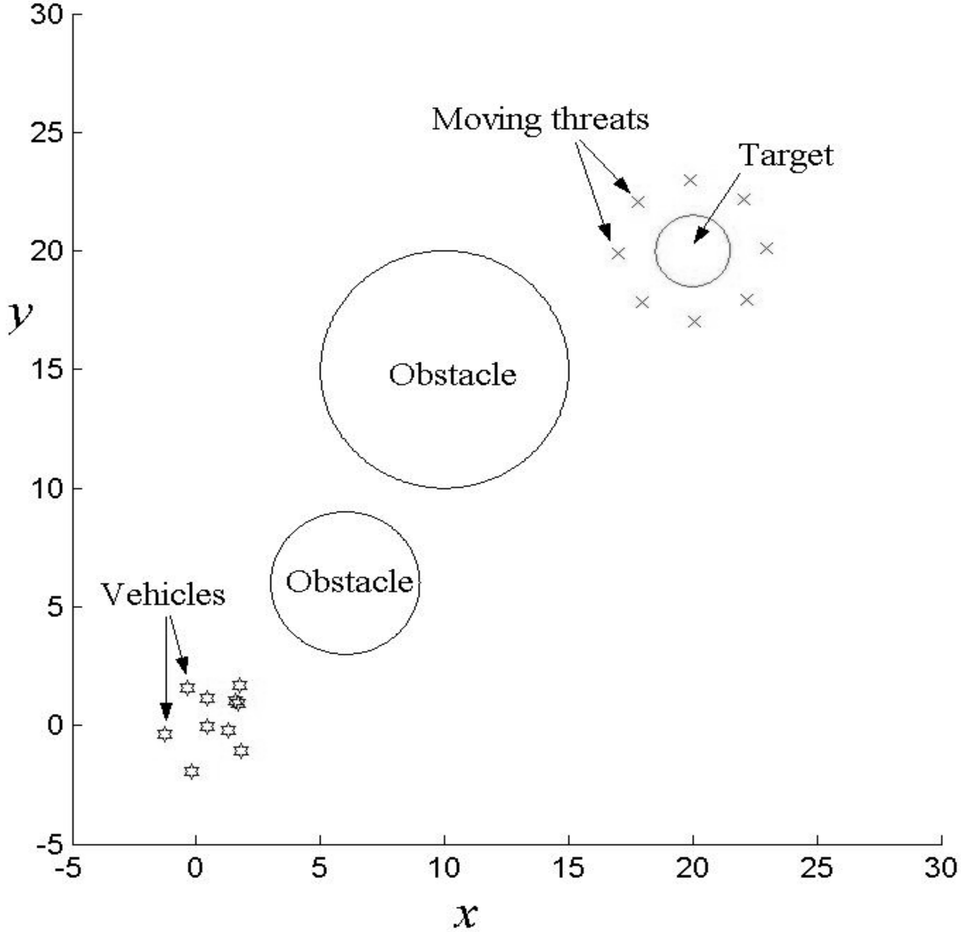
Behavior under Attraction and Repulsion (II)



Vector field on the plane.

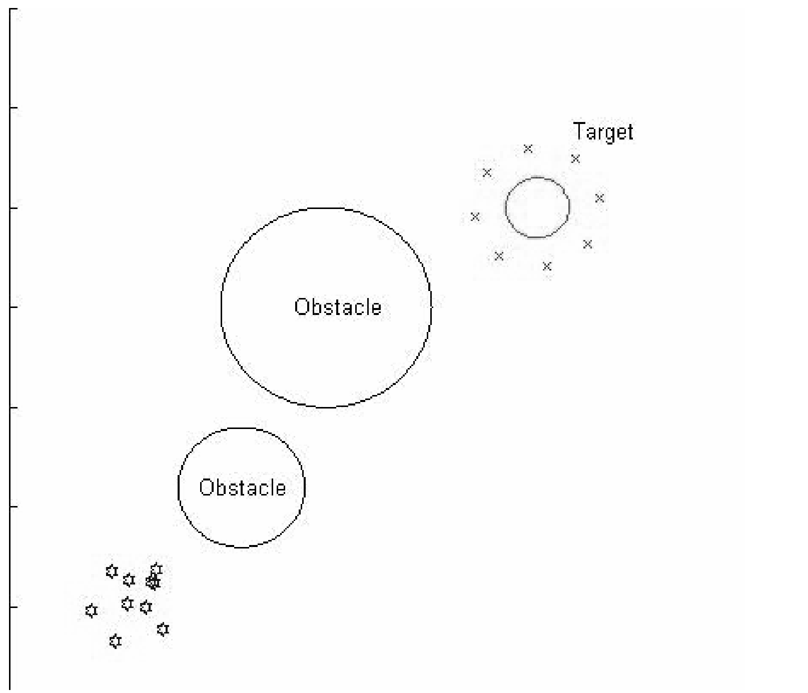
- Scenario II: one target, one obstacle. No restriction on the initial position of the vehicle.
- Question: can the vehicle move toward the target? How does ? affect the behavior in this case?
- Answer:
  - The only equilibrium which might trap the vehicle is unstable. Hence the vehicle will not be trapped by any local minimum of the potential function;
  - However, there is a detour region (shaded area) where the vehicle needs first to move in a direction opposite to the target. The larger ?, the smaller this region.

Simulation Scenario

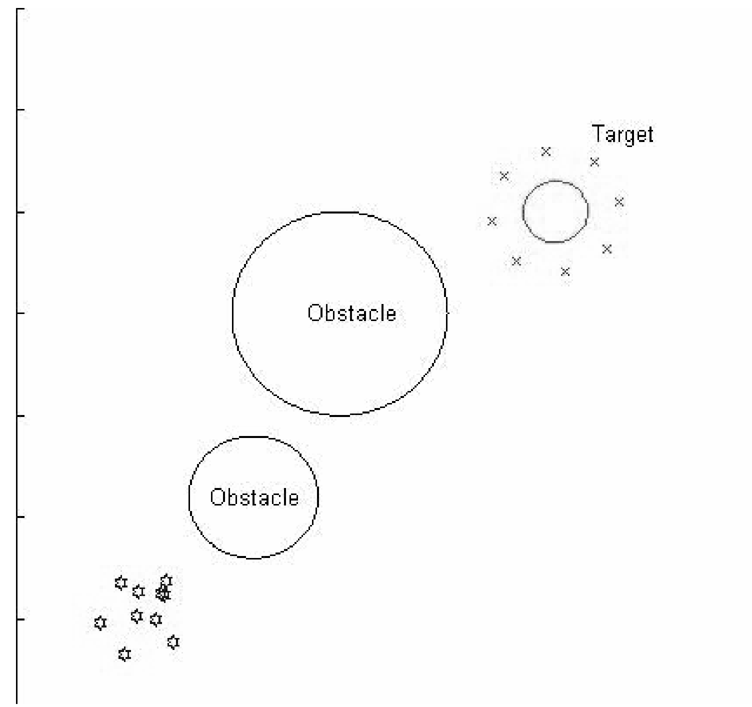


- 10 vehicles randomly initialized
- 2 obstacles
- 1 circular target area
- 8 moving threats guarding the target with a speed 1.5 times that of the vehicles

Effect of the weighting constant $?_m$ for the moving threats (other weighting constants held fixed)

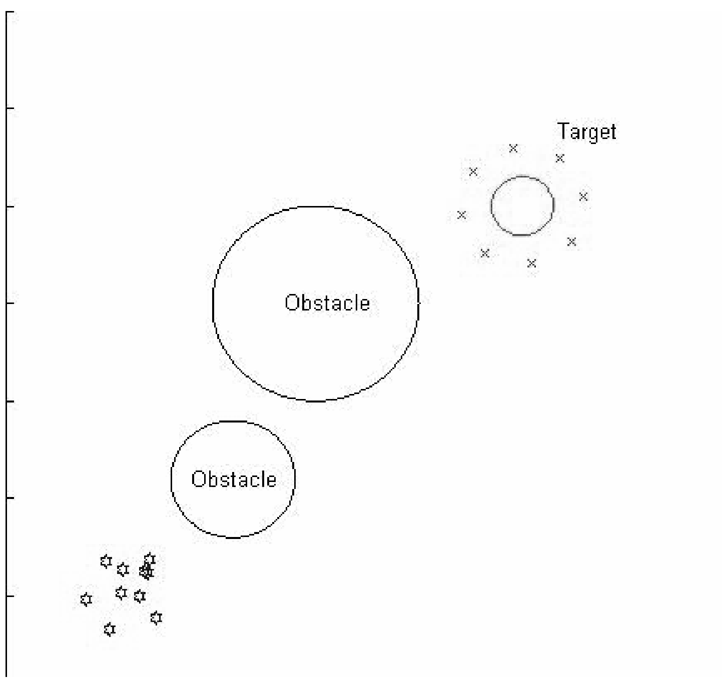


(a) $?_m$ =10 (very small). The vehicles paid little attention to the threats and four of them were killed.

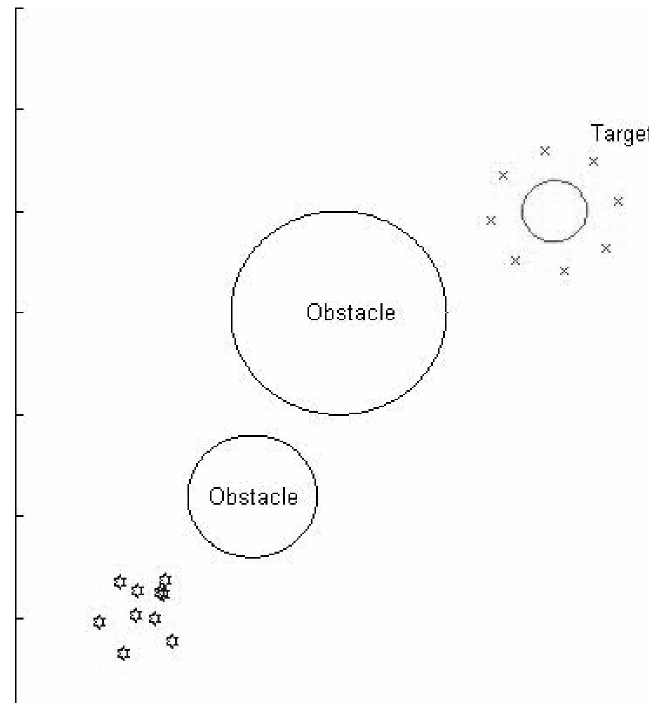


(b) $?_m$ =50. The vehicles paid more attention to the threats and only one of them was killed.

Effect of the weighting constant $?_m$ for the moving threats (other weighting constants held fixed)--continued

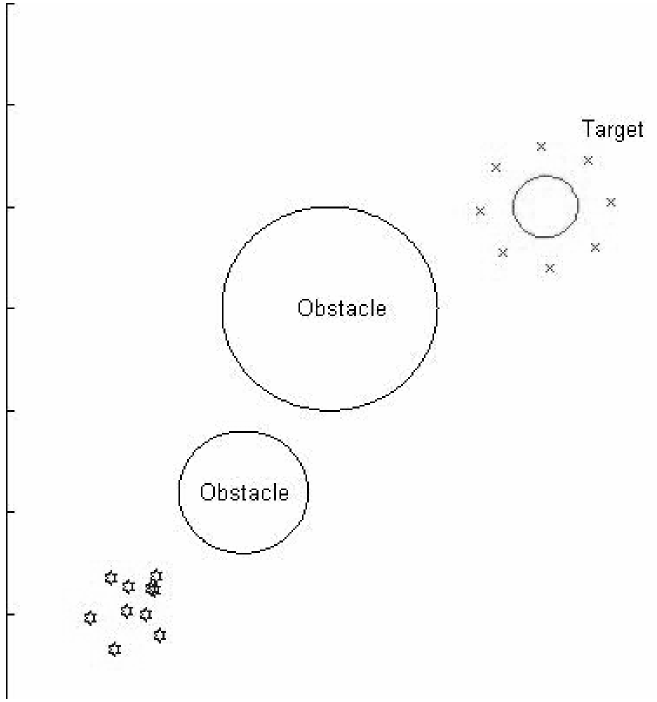


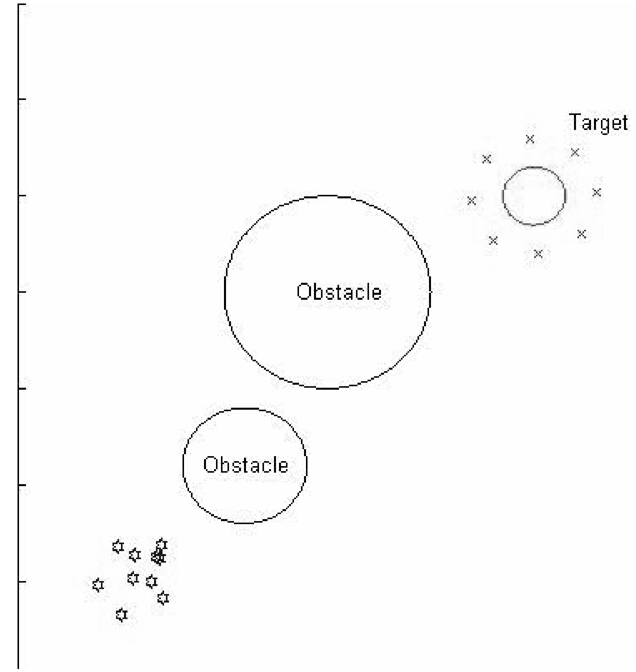
(c) $?_m$ =200. All vehicles entered the target successfully and in a timely manner.



(d) $?_m$ =2000 (very large). Some vehicles were not able to enter the target since most attention was on evasion from the threats.

Effect of the weighting constant $?_o$ for the obstacles (other weighting constants held fixed)





(a) $?_o$ =1000. One group of vehicles took the shorter path and passed the obstacle valley.

(b) $?_o$ =5000. No vehicle took the shortcut (some actually took the detour).

Conclusions

- A decentralized approach to coordination and control of multi-vehicles was explored using potential functions
  - Simple (only local /static information needed)
  - Flexible and robust (of vital importance in dynamic/uncertain environments)
- Analysis was conducted on
  - Stability of equilibrium formations
  - Single vehicle behavior under attraction and repulsion (in particular, effect of the weighting constant)
- Simulation results demonstrated that
  - Emergent behaviors arise from local interactions
  - The behaviors can be modified through the weighting constants

Future Work

- Take into account the dynamics of vehicles (with various constraints)
- Explore a hybrid sensing/decision/control architecture
- Quantify the effect of weighting constants, and streamline the design of potential functions given mission requirements.

Technology Transfer

- We continued interacting with researchers from Telcordia, Johns Hopkins, BBN, and FCS, in an effort to further develop the application of our dynamic clustering methods using value-function non-variation in autoconfiguration and routing.
- After several meetings with ARL personnel, very knowledgeable and leading the FCS program, in an effort to understand and characterize mobility patterns of future Objective Force and FCS systems, we have adopted a more appropriate mobility description which utilizes trajectories for each node in the network of control systems according to their mission and capabilities.
- These adjustments were incorporated in the formulation of swarm intelligence based coordination algorithms and in the problem involving the coordination, collaboratively and in a distributed and asynchronous manner, of a set of mobile vehicles equipped with sensors and communications towards achieving a specific goal described in terms of geographic advancement and territory control. Results will be transferred to the ARL and the FCS program.

Publications

1. B. Frankpitt and J.S. Baras, “Nonlinear Robust Control with Unknown System Models: HMM Formulation”, submitted to *SIAM J. Control and Optimization*, 2002.
2. B. Frankpitt and J.S. Baras, “Nonlinear Robust Control with Unknown HMM Models: Convergence and Learning”, submitted to *SIAM J. Control and Optimization*, 2002.
3. C. Zhang, *Decomposition of Large Scale Dynamic Programming By State Aggregation*, Ph.D. Thesis, Electrical Engineering and Computer Engineering Department, University of Maryland College Park, August 2002; available as *Technical Report, Institute for Systems Research*, University of Maryland, College Park, 2002.
4. C. Zhang and J.S. Baras, “A New Adaptive Aggregation Algorithm for Infinite Horizon Dynamic Programming”, *Proceedings of the 11th Mediterranean Conference on Control and Automation (MED’03)*, Rhodes, Greece, June 18-20, 2003
5. J.S. Baras, X. Tan and W. Xi, “Jointly Optimal Quantization, Estimation, and Control of Hidden Markov Chains”, to appear *Proc. 2003 IEEE Conference on Decision and Control.*
6. J.S. Baras, X. Tan, P. Hovareshti, “Decentralized Control of Autonomous Vehicles”, to appear *Proc. 2003 IEEE Conference on Decision and Control.*