Probabilistic Models in Large-Scale Human-Machine Networked Systems

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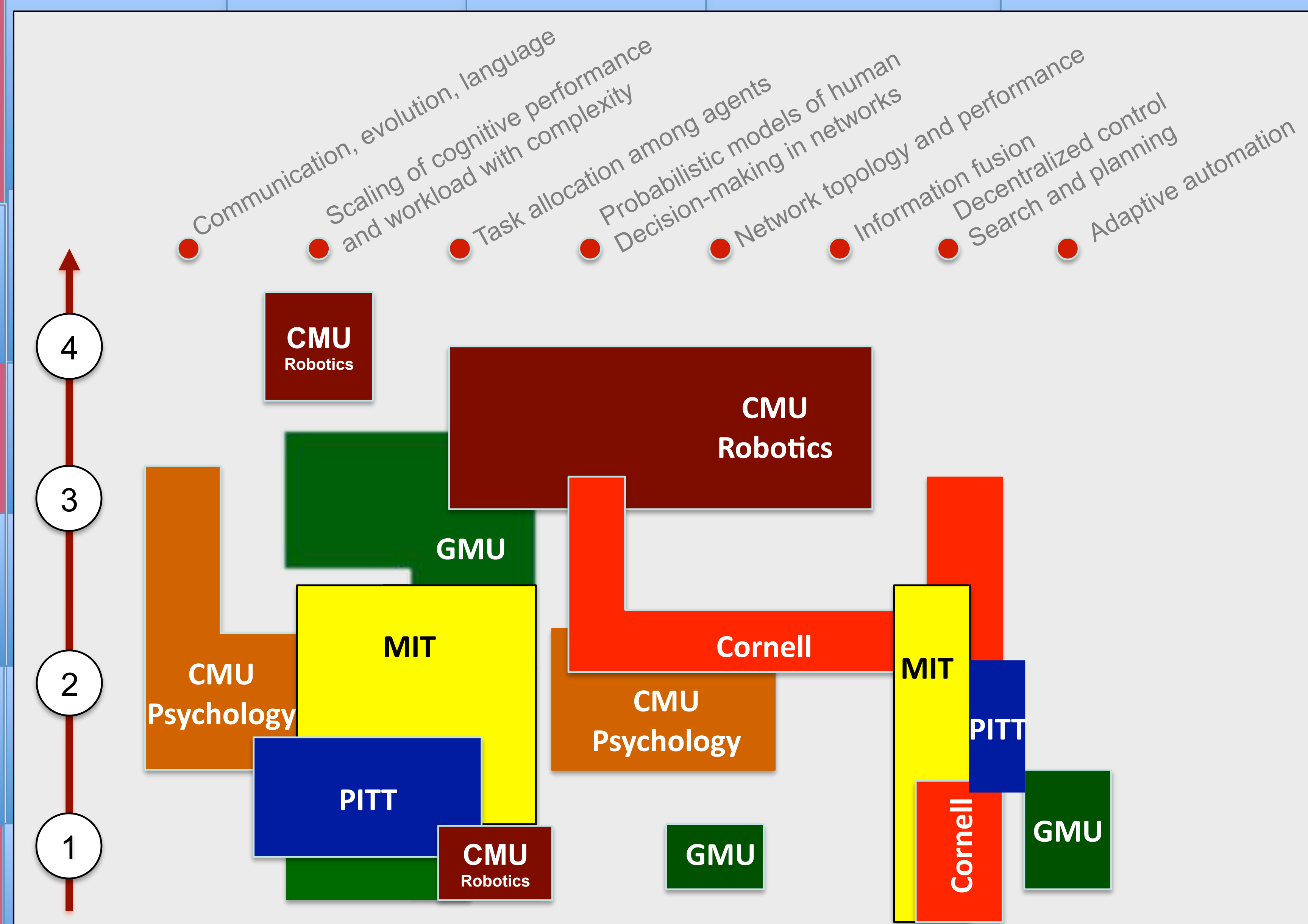
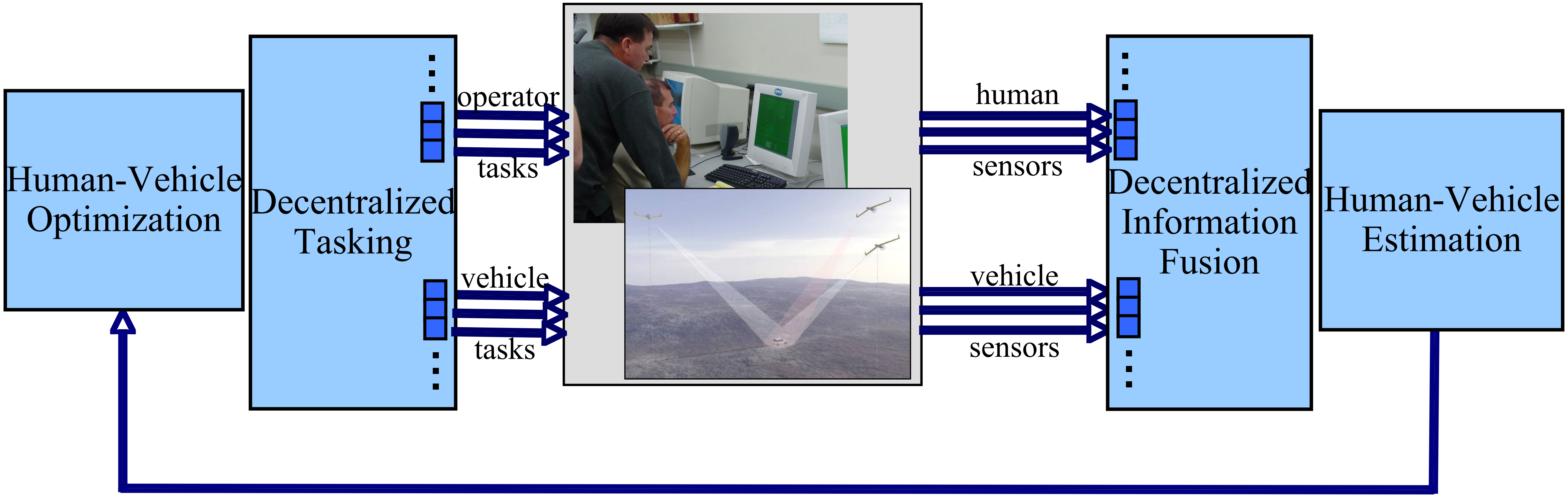
Cornell University

Cornell's Current Work

	Cornell	MIT	GMU	Pitt	CMU Robotics	CMU Psychology
Scaling of cognitive performance and workload			Level 1,3	Level 1,2	Level 1	Level 2
Task allocation among humans/agents		Level 1-2.5	Level 1-3	Level 1	Level 1,3	
Probabilistic models of human decision-making in network situations	Level 1,2					
Decentralized control search and planning						
Information fusion	Level 1,2					
Network performance as a function of topology						
Communication, evolution, language						
Adaptive automation	Level 1,2					



Cornell Program Motivation



- Goal: Explore how to integrate humans as nodes in information networks with robots?
  - Decentralized fusion
  - On-line inference of team performance
  - Decentralized/hierarchical task planning

Specific Research Goals

1. Develop probabilistic modeling methods to capture human decision making
   - Variety of complexities, data conditions, over time

2. Develop performance metrics for networks of human-vehicle systems
   - Information flow to/from human node

3. Develop and validate on-line methods for:
   - inferring network performance: interaction, mistakes
   - network adaptation: e.g information exchange, tasking

Outline

- Motivation and Objectives
- Progress:
  - –Decision Modeling
  - –On-line inference: Discrete and continuous fusion
  - –Sensor Fusion
    - large decentralized network
    - robots only, humans only
    - robots and humans
- Future work
  - –Collaborations

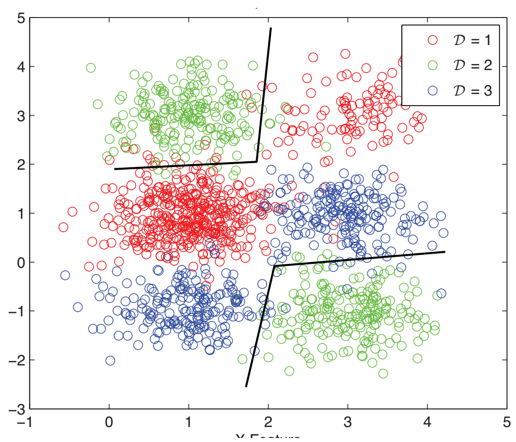
Decision Modeling Work

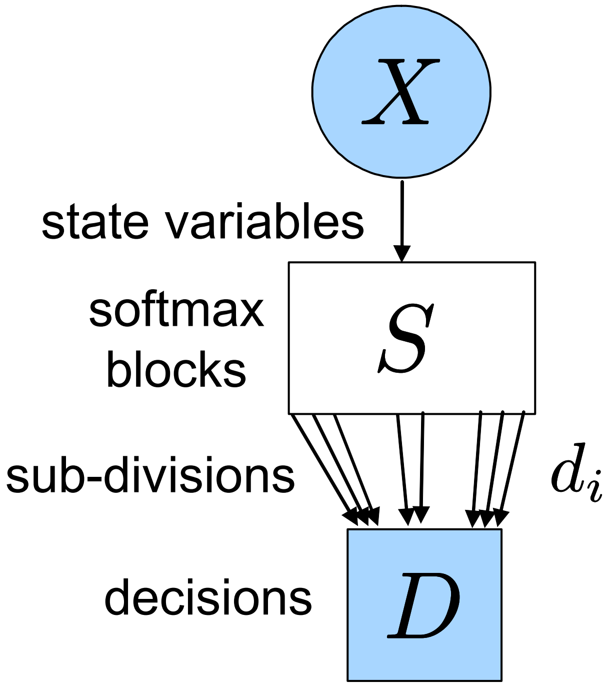
- *MMS model for discrete decisions
  - –validation on benchmark and RoboFlag human data
- Currently attempting to model all human decisions in RoboFlag games
  - –discrete and continuous
  - –hold out validation: how well can we do and what are the limitations?

* presented in this talk

Multimodal softmax (MMS)

ACC 2008





- Discriminative modeling of complex posterior distributions w/o relabeling data
  - i.e. no a priori clustering
- Divides (nonconvex) multi-modal decision data into convex sub-divisions
  - enables rich decision models
- Marginalize out *S* to enable consistent optimization, and create likelihoods:

$$\mathcal{P}(D = d_i | X) = \sum_{j=1}^{s_i} \mathcal{P}(S = d_{ij} | X)$$

- Asymptotic guarantees on convergence to the true model parameters, given an infinite set data

MMS Validation: RoboFlag and Benchmarks

SMC 2009 (in review)

TABLE 3
RoboFlag Classification Error Statistics (mean % error, standard deviation).

Case	Softmax	SVM	MMS	GMM-A	GMM-B	HSS-A	HSS-B	Best ME
1	19.09 ± 0.63	**15.71 ± 0.48**	17.11 ± 0.74	17.91 ±0.69	16.83 ±0.47	18.35±0.95	19.17±1.03	16.27 ±0.43 (ME2)
2	23.23 ± 0.68	18.53 ± 0.83	**18.01 ±0.85**	21.40 ±0.77	20.65 ± 0.77	19.36±0.77	19.21±0.74	18.47 ±0.68 (ME3)
3	61.93± 0.28	40.62 ± 1.11	40.25 ±1.06	43.12 ±1.76	39.69 ± 1.51	41.93±1.13	43.22±1.11	41.42 ±0.91 (ME4)

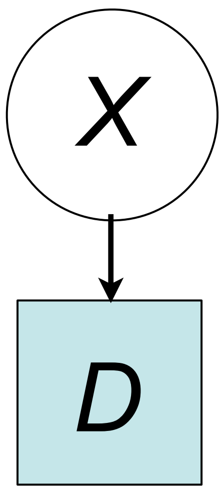
TABLE 4
RoboFlag Training Costs (mean training time (CPU secs), parameter count).

Case	Softmax	SVM	MMS	GMM-A	GMM-B	HSS-A	HSS-B	Best ME
1	2.24, 39	173.06, 1222	16.21, 143	0.56, 13167	0.90, 21546	11.61, 143	34.51, 234	71.93, 104
2	1.89, 39	135.52, 1404	5.30, 104	0.37, 9576	0.37, 10773	6.06, 104	7.86, 117	96.47, 156
3	4.63, 78	40.53, 1428	9.42, 143	0.27, 13167	0.73, 21546	18.45, 143	48.96, 234	219.48, 208

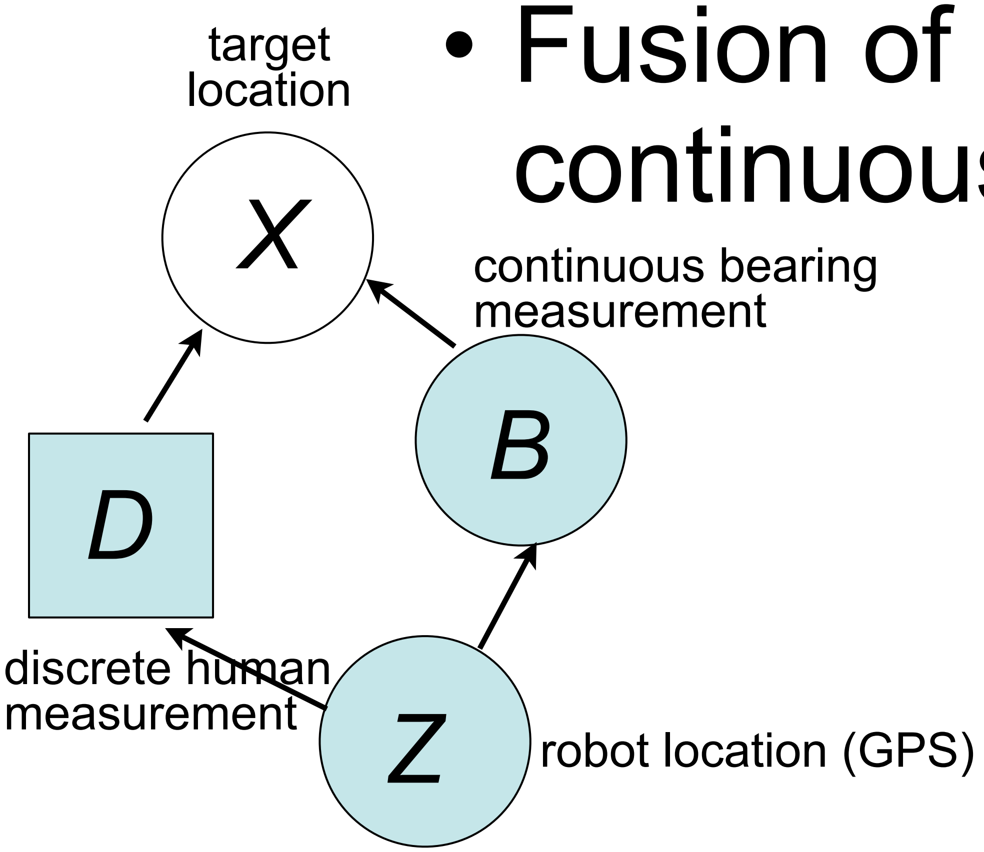
- RoboFlag decision modeling demonstrates good results:
  - error statistics, training time: compared to SOA classifiers
- Benchmark data (not shown) demonstrate similar results

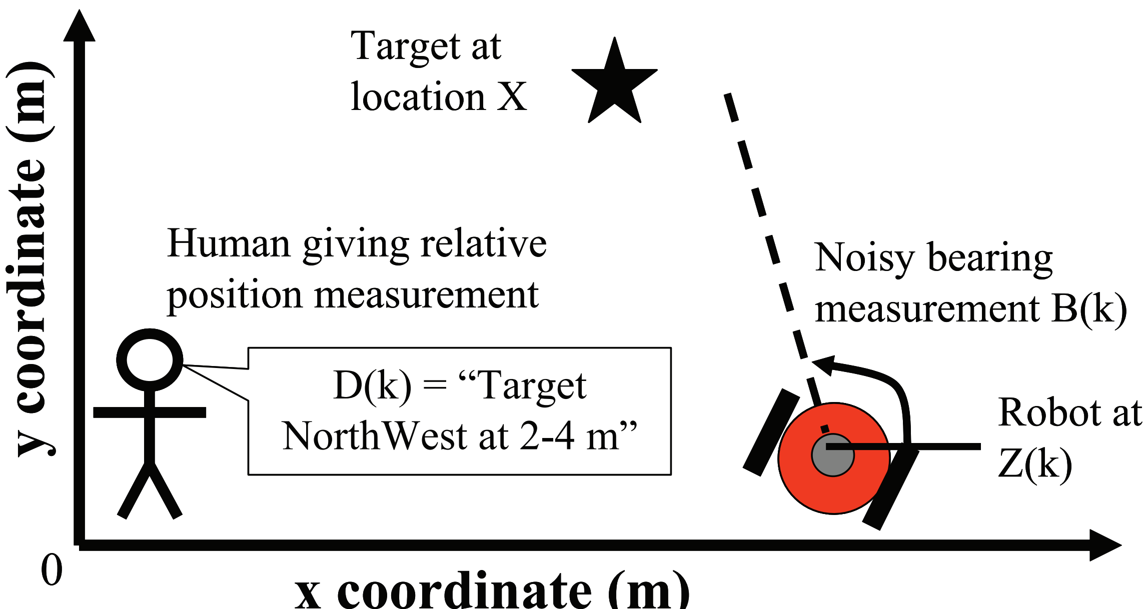
+ produces probabilistic model, - not for problems like vision

Use Models for Inference

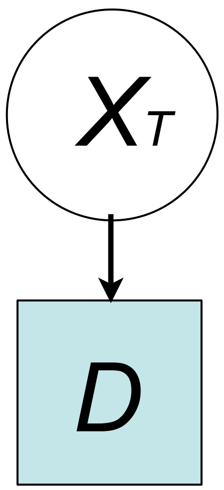


- Given a decision *D*, can we infer information about the system *X* (that is not measured)?
  - inferring operator intent
  - inferring individual/team performance
    - To enable: operator assistance, adaptive tasking
- Fusion of discrete human observations and continuous robot measurements





Inference Example



- Given discrete decision *D*, infer continuous X
- Unfortunately, joint pdf is no longer Gaussian and the integral has no analytical solution

$$p(X_T|D) = \frac{p(X_T)P(D|X_T)}{\int_{-\infty}^{\infty} \boxed{p(X_T)P(D|X_T)} dX_T}$$

$$p(X_T, D)$$

- Must resort to approximation:
  - discretization: does not scale with X
  - Monte Carlo: SOA, but can be inefficient or slow
  - bounds: approximate joint pdf

Inference using Local Variations

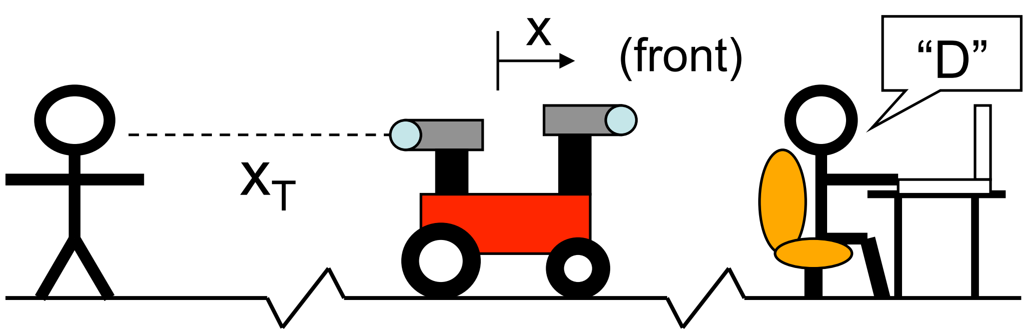
- [Bouchard 2008]: for a Gaussian prior, approximate joint PDF by Gaussian lower bound
  - –Fast iterative estimation of lower LBound
  - –Use for fusion, approximate posterior

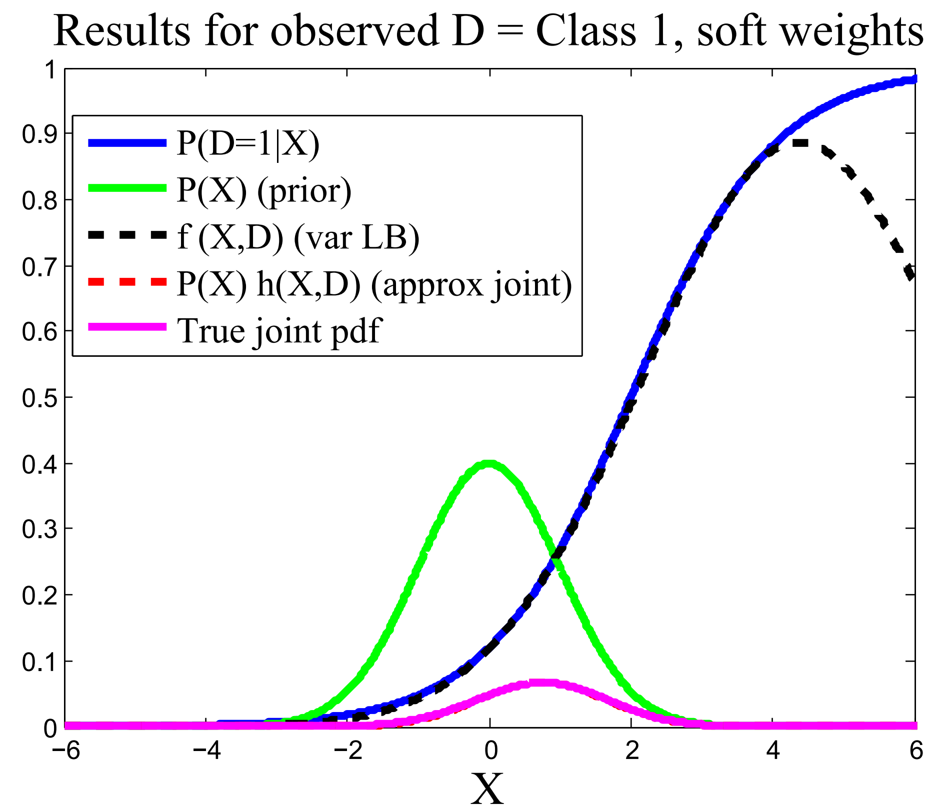
Posterior Mean and Variance:

Exact: -6.4158, 1.6365

Approx.: -6.4116, 0.4069

- Example: Localization of person from robot with camera
  - – D: {“behind and far away”, “ behind and nearby”, “next to”, “in front and nearby”, “in front and far away”}





Sensor Networks and Fusion

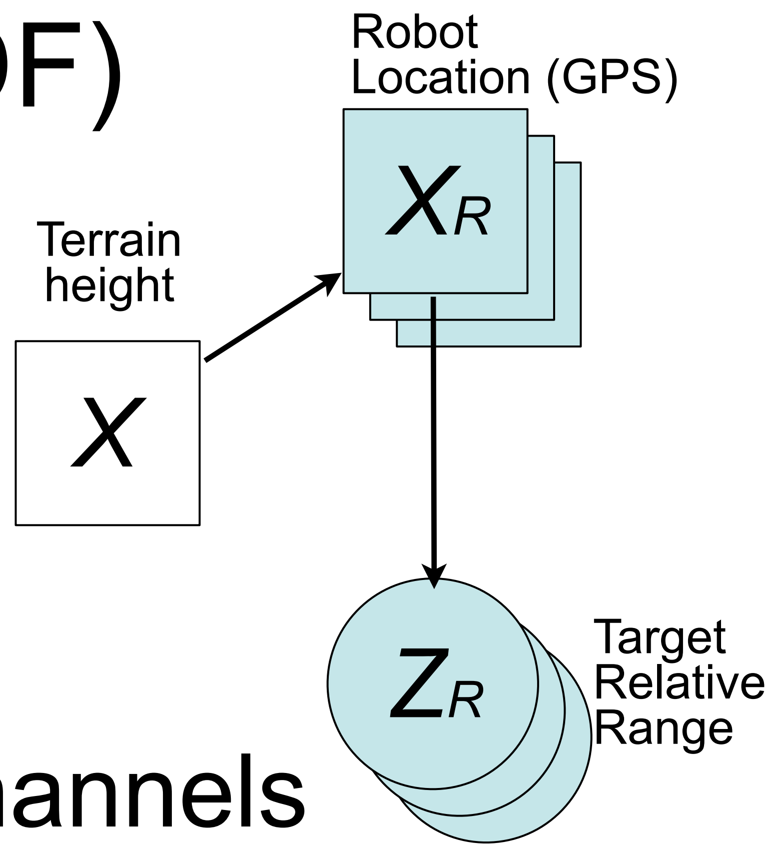
- *Decentralization using channel filter
  - –scales well with nodes in a tree structure
- *Hierarchical fusion
  - –humans for ID, robots for mapping
- *Sensor fusion theory and experiments
  - –humans only network
  - –robots only network
  - –human and robot network

* presented in this talk

Decentralized Fusion

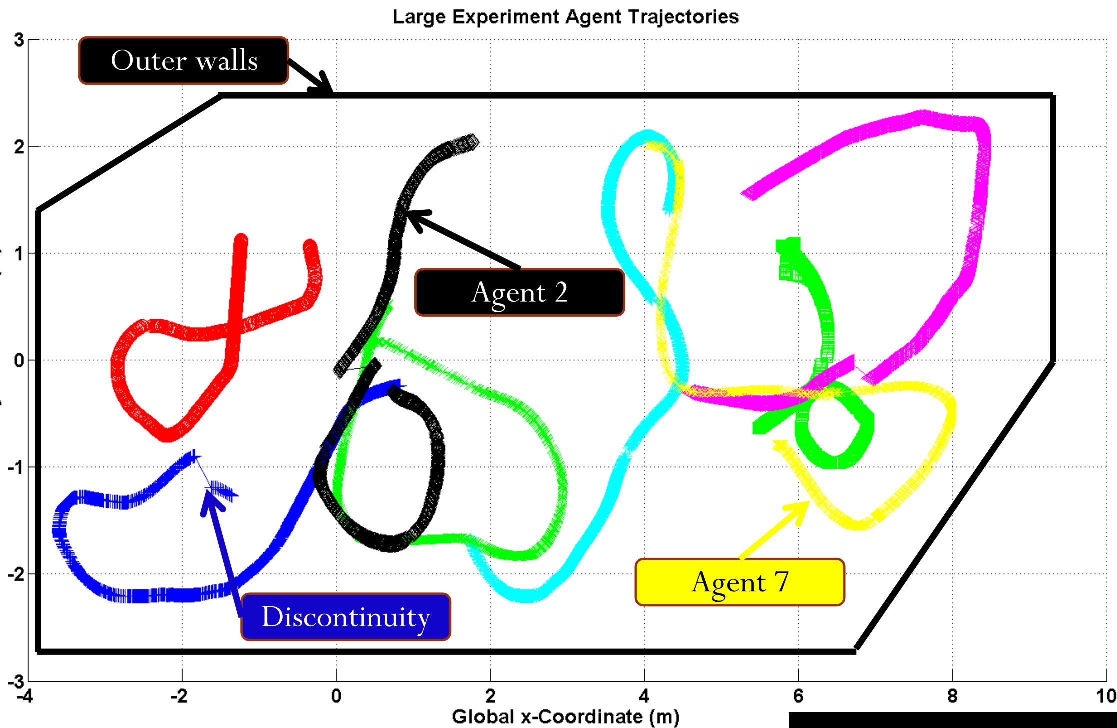
Fusion 2009

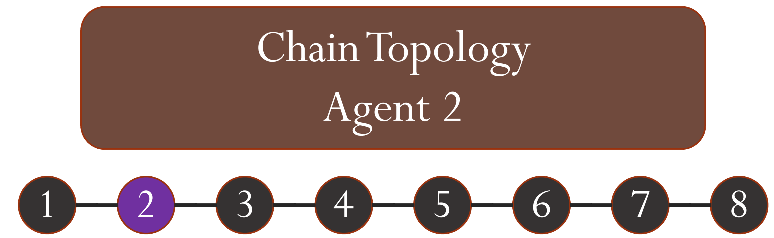
- Decentralized terrain mapping (PDF)
  - grid based;
  - requires tree like topology
  - could be used for: localization, ID,...



- Channel filter
  - Monitors data over communication channels
  - Orig developed for Kalman Filters (Durrant-Whyte)
  - Requires tree-like comm architectures
  - Scales with the number of nodes (humans, robots),
  - Yet achieves centralized soln even in presence of communication uncertainties (delays, drops)

Collaborative Mapping w/ Large Network

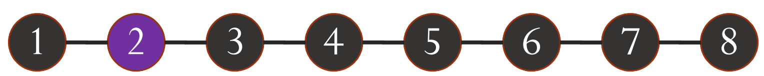




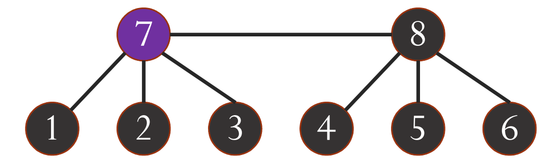
- Vehicle (pose, attitude), sensor (align, noise) uncertainties
- TCP-IP
- Guarantees even in presence of communication uncertainties
- Results shown for 8 robots

Compare Topologies: Collaborative Mapping w/ Large Network

Chain Topology
Agent 2

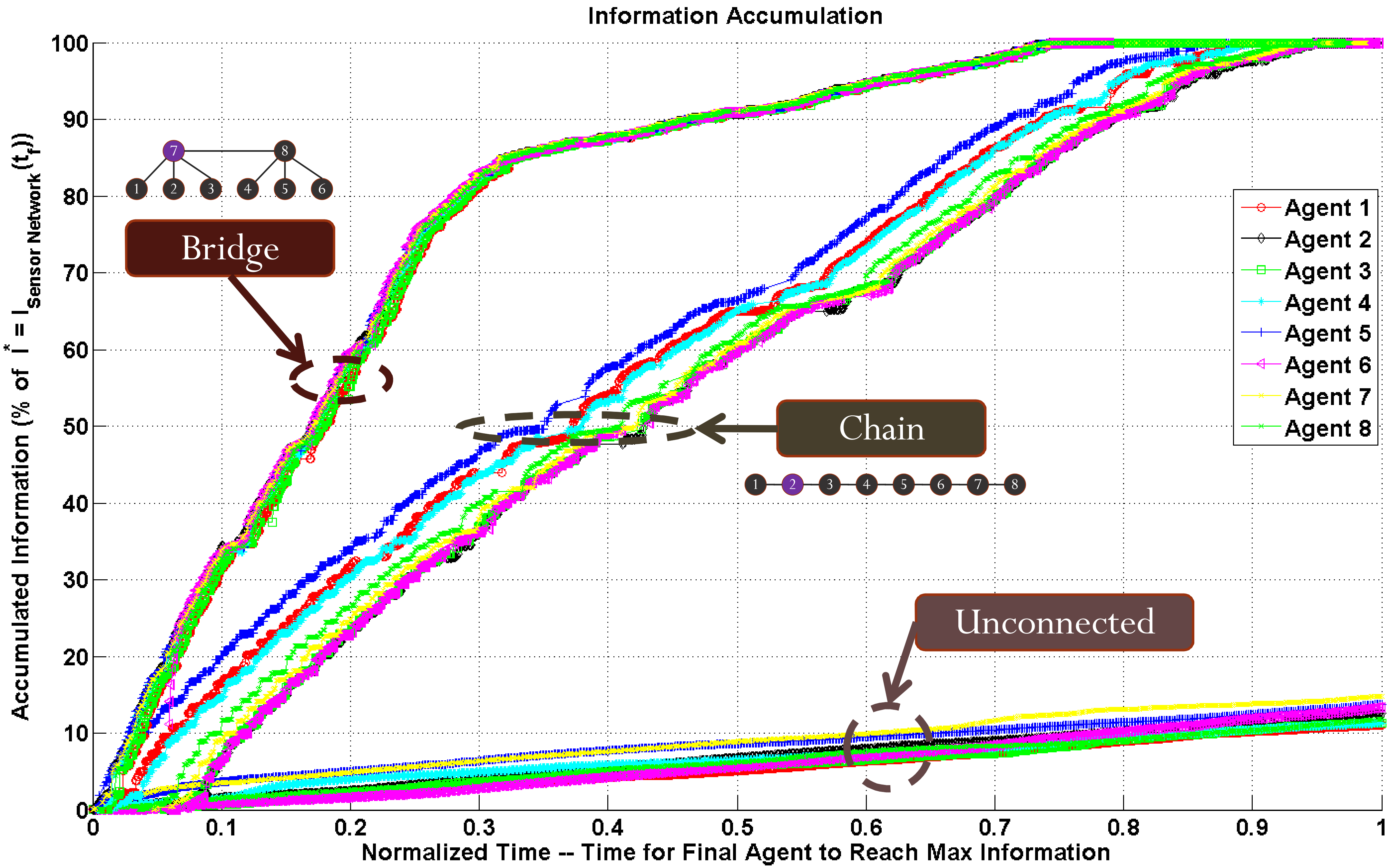


Bridge Topology
Agent 7



- Bridge network achieves results faster
  - Fewer hops for the data

Compare Topologies: Collaborative Mapping w/ Large Network



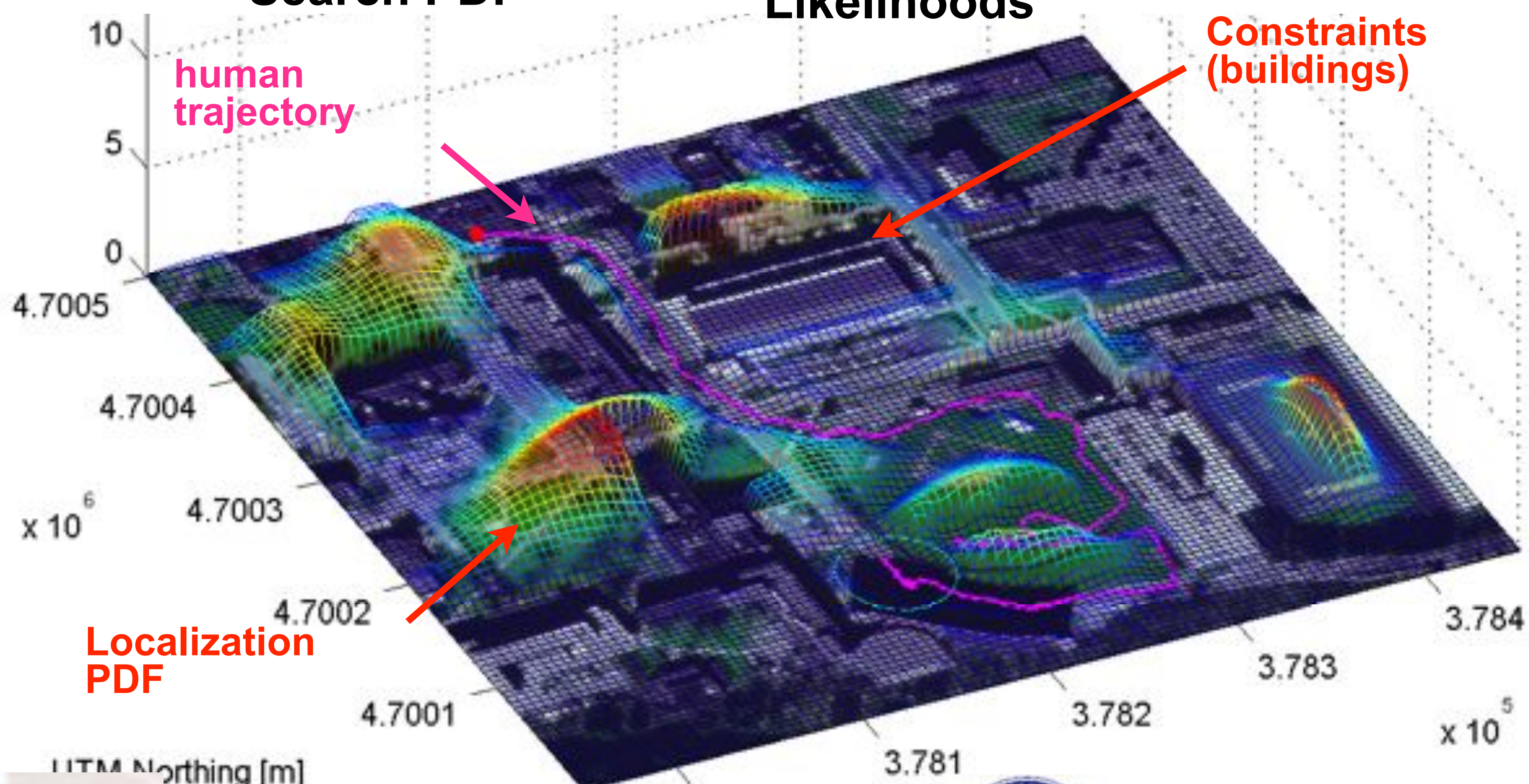
- Topology important in terms of speed of response

Network of Humans Searching: Decentralized Data Fusion

- Similar to robots: With human detection model, "fuse" human observations ***exactly*** like other measurements:

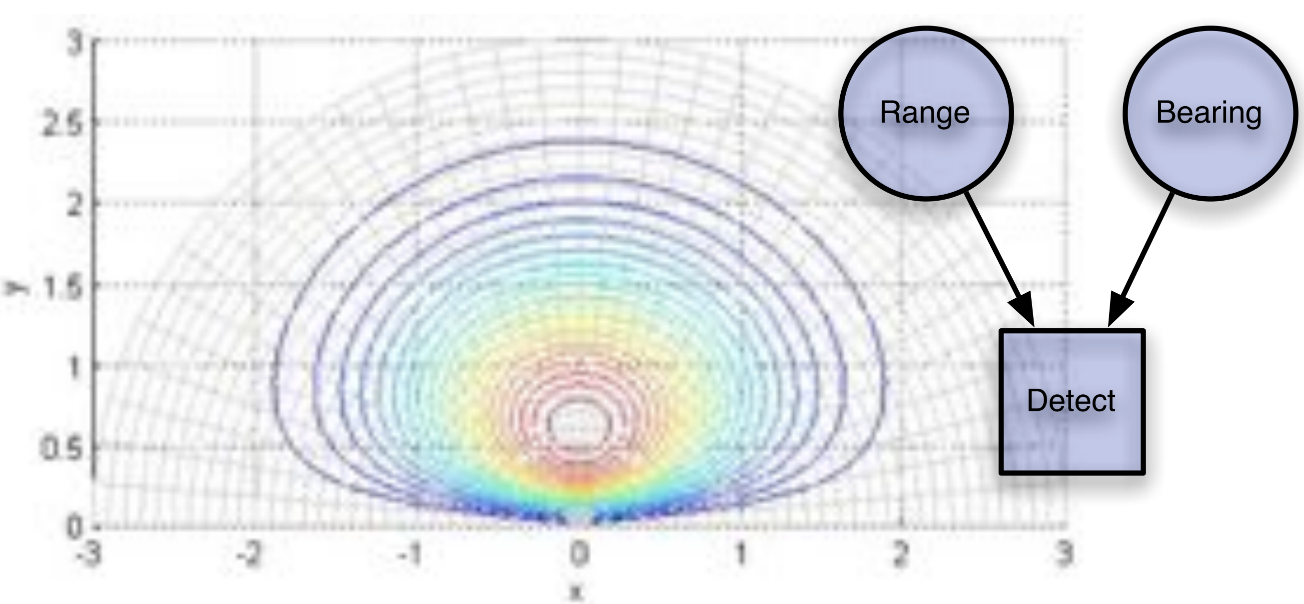
$$\underbrace{p(\mathbf{x}_k|\mathbf{I}_k)}_{\substack{\textbf{Fused}\\ \textbf{Search PDF}}} = \underbrace{p(\mathbf{x}_k|\mathbf{I}_{k-1})}_{\substack{\textbf{Predicted}\\ \textbf{Search PDF}}} \prod_{i=1}^{N_s} \underbrace{p(\mathbf{z}_k^i|\mathbf{x}_k)}_{\substack{\textbf{Measurement}\\ \textbf{Likelihoods}}}$$

Satellite Map, Overlaid with Search PDF



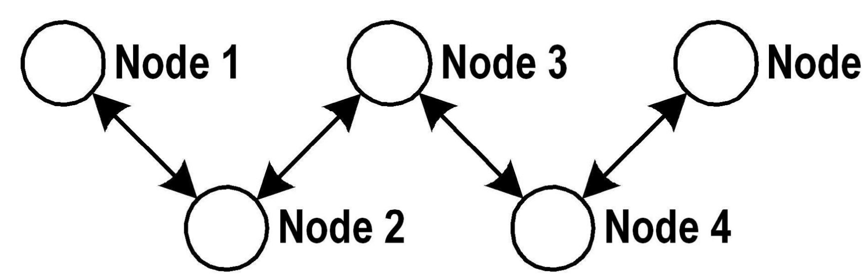
Fall 09 Experimental Campaign: Network of Five Humans Searching

- Five Human nodes
- (Uncertain) measurements from each human operator
  - Localize (GPS)
  - Heading (compass)
  - Human detection model:



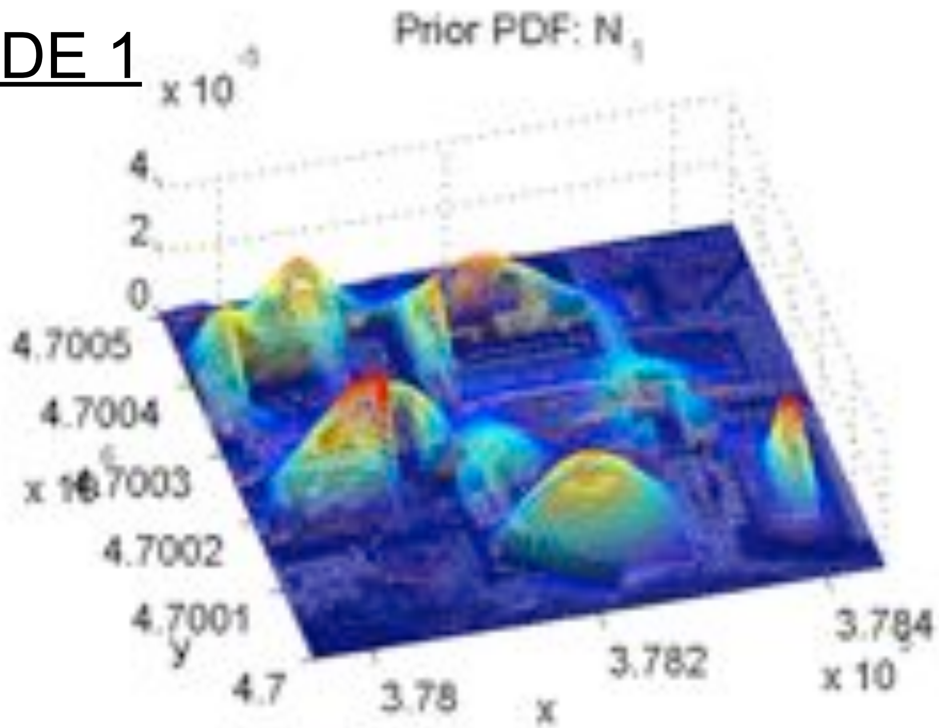
- Converges to centralized soln

Network:

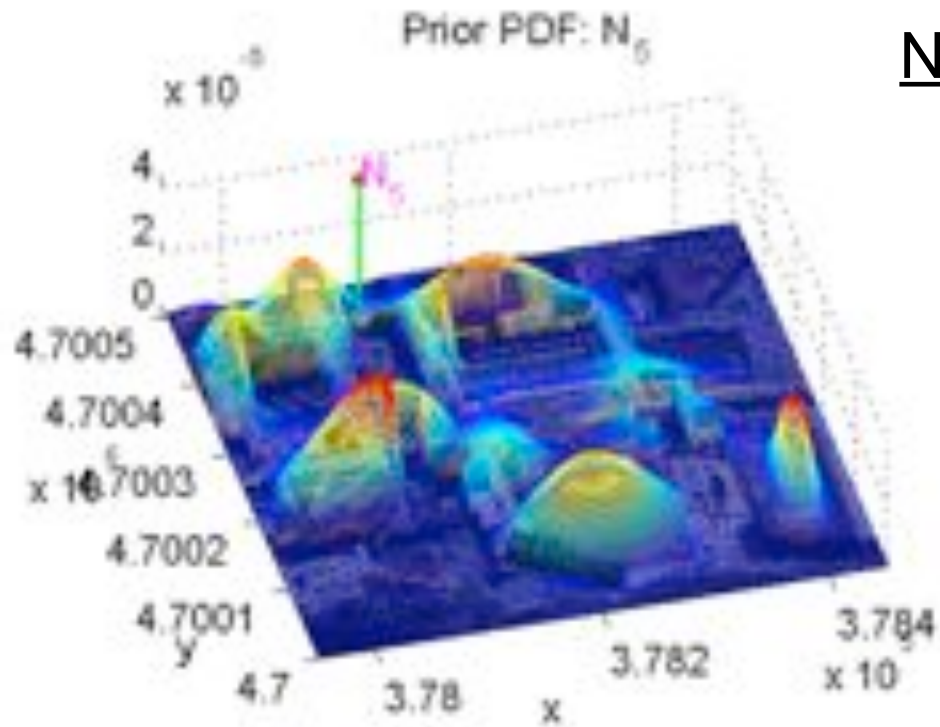


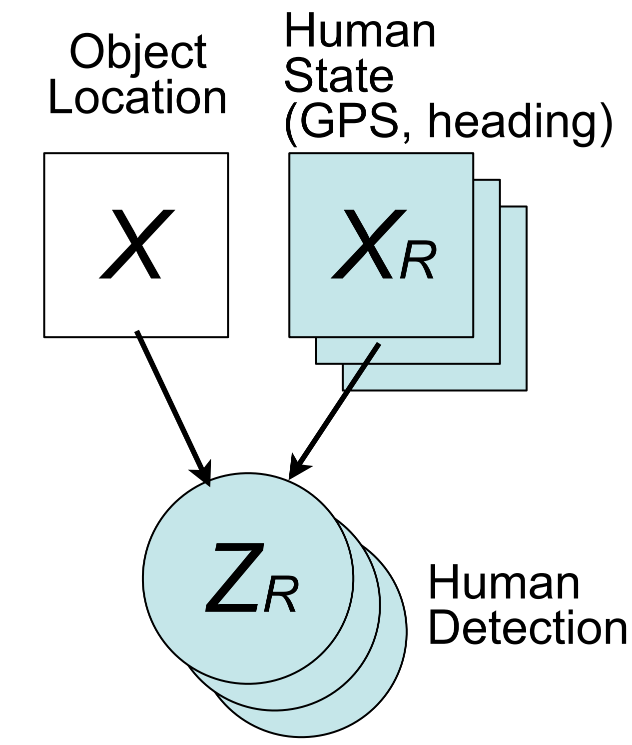
Five People Searching for Five Targets

NODE 1

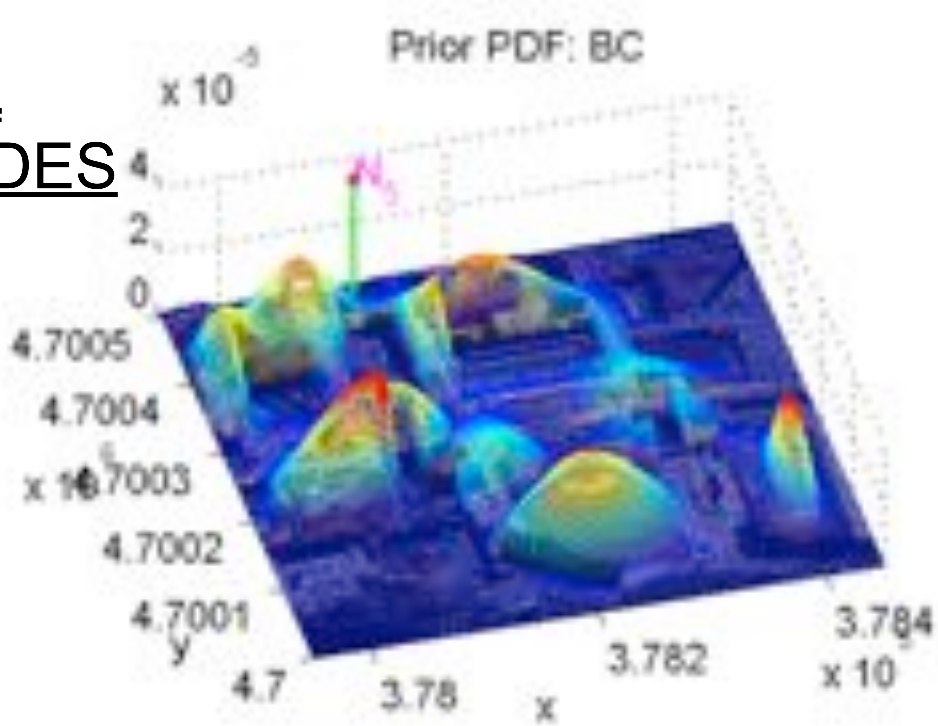


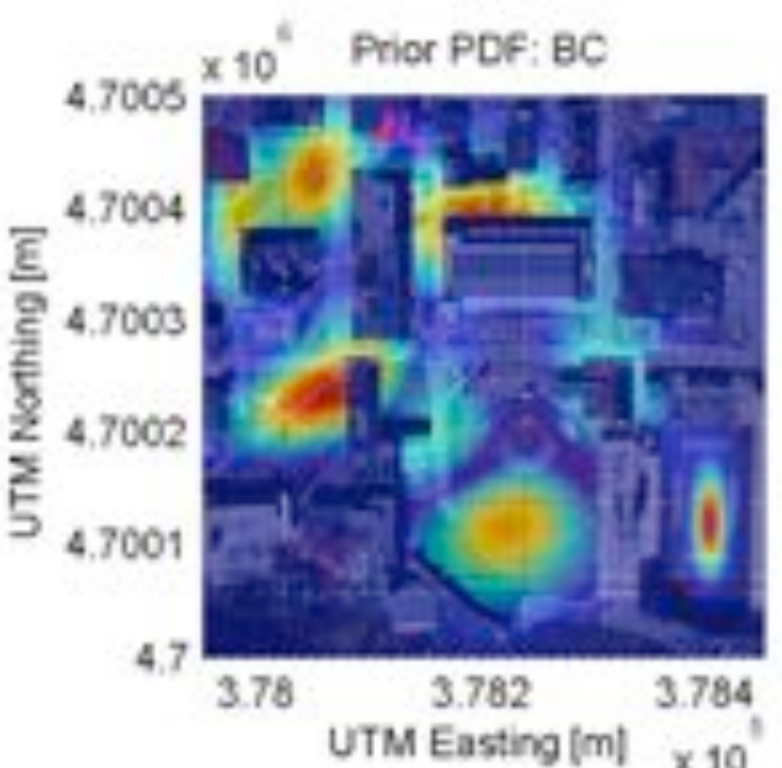
NODE 5



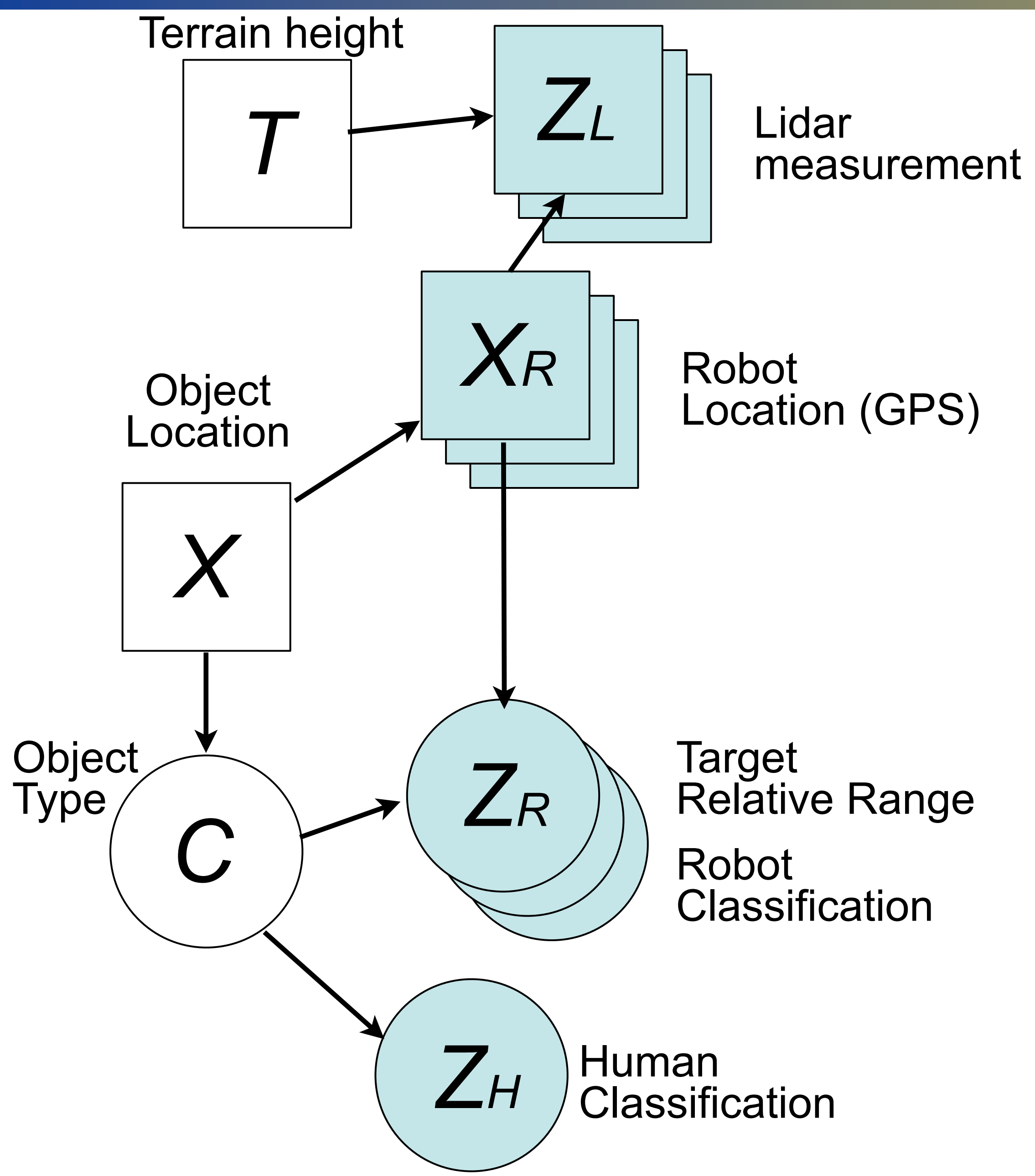


ALL NODES





Human+Robot Fusion (and Tasking)



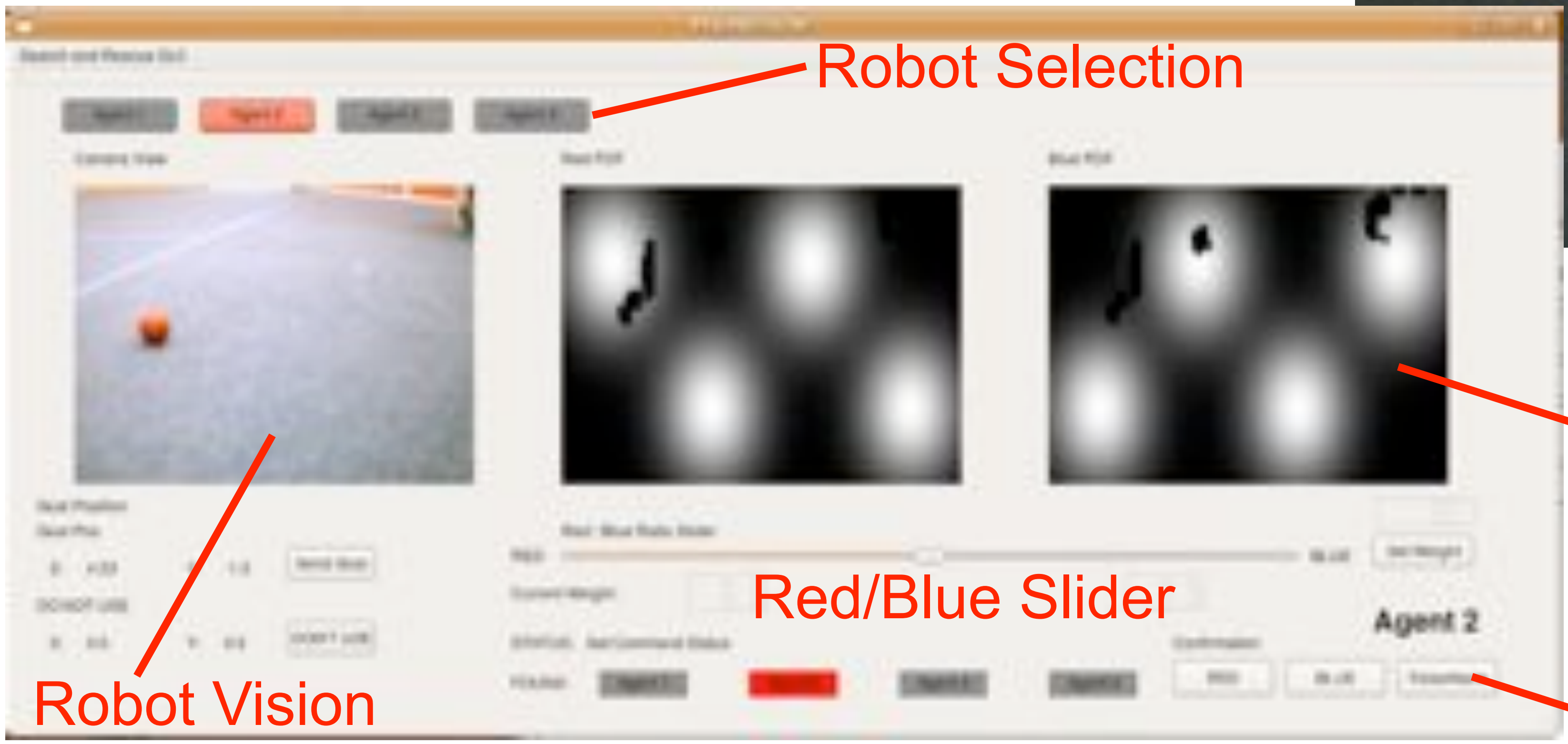
- Both human, robot info:
  - Robot: range, ID
  - Human: ID
- Object locations:
  - Continuous
  - Channel filter for fusion
- Object Type:
  - Discrete (Blue, Red)
- Robots: Search over joint PDF
- Humans: Strategic Control

Mission Goal:

$$p(X, C | X_R, Z_R, Z_H)$$

Hybrid: Strategic Tasking/Sensing

- Operator GUI:
  - Local vision, tasking



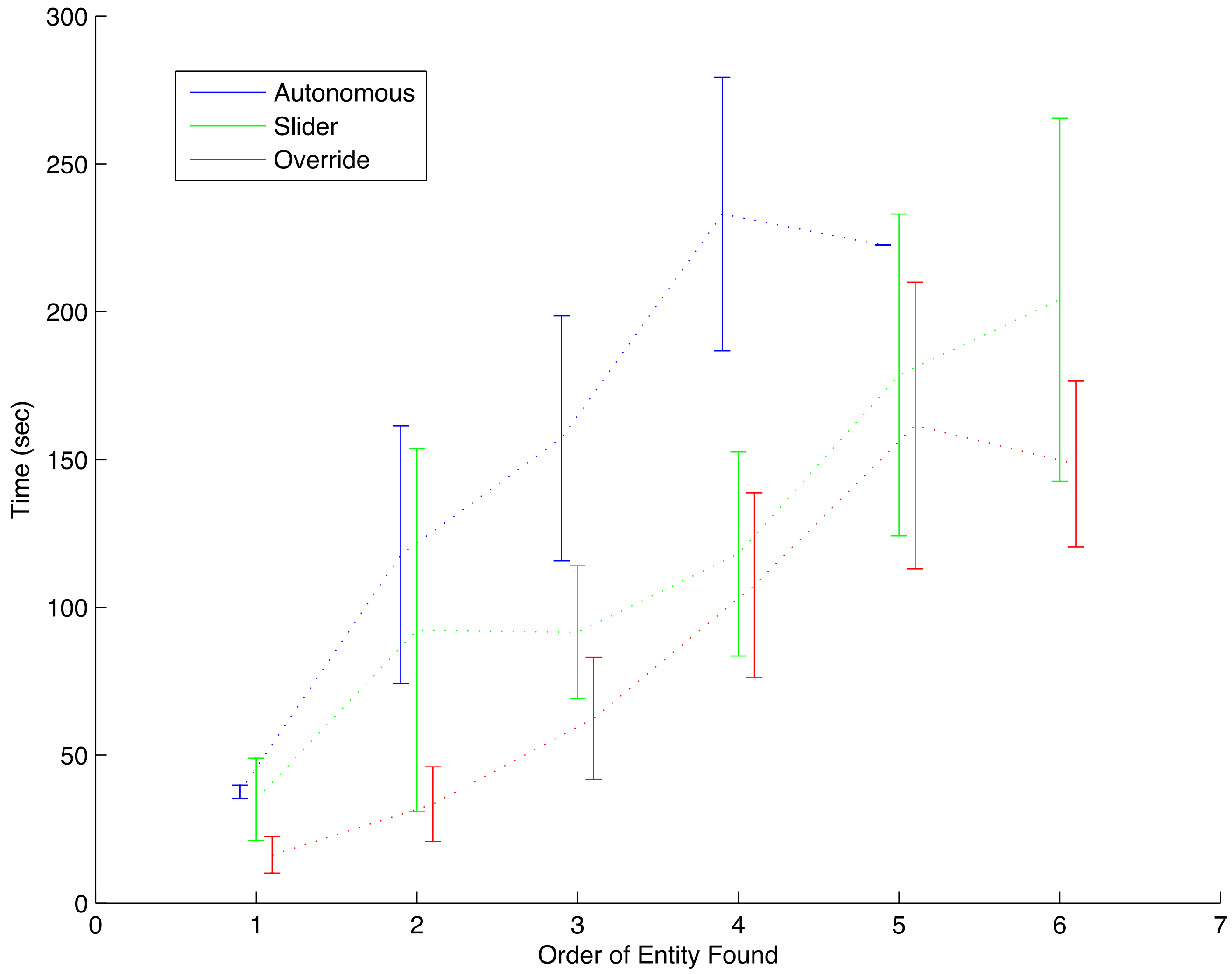
- 4 Segways
  - GPS,
  - vision, lidar

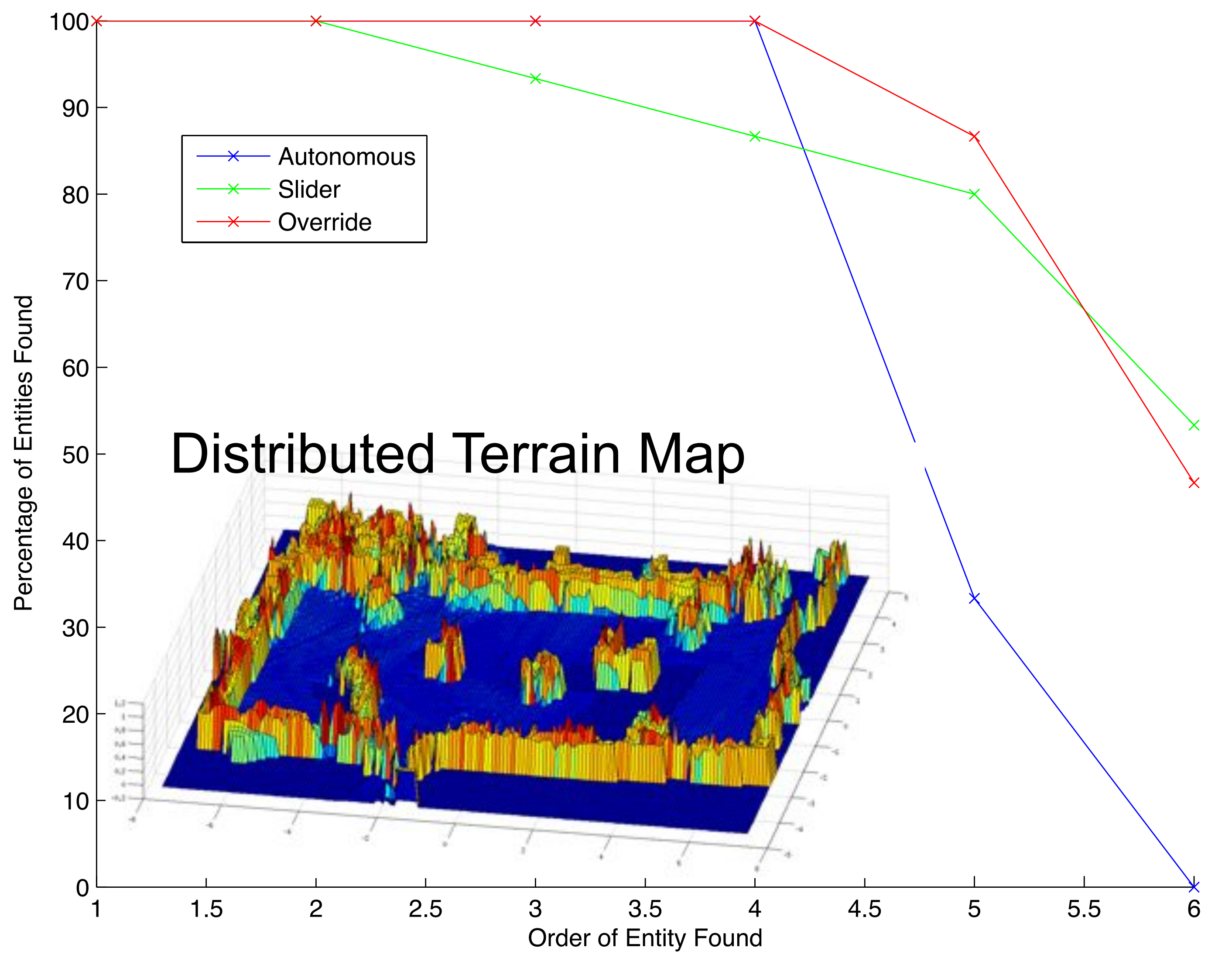
- Mission goal: Locate and classify objects
  - Two types (red, blue)
  - a priori PDFs of location of each

Outdoor Testing

- Human Trials:
  - Autonomous
  - Slider (Red,Bl)
  - Sldr+OverRide
- Human always performs final classification
- 5 min trials
- 4/2, 3/3, 2/4 red/blue

Initial Results

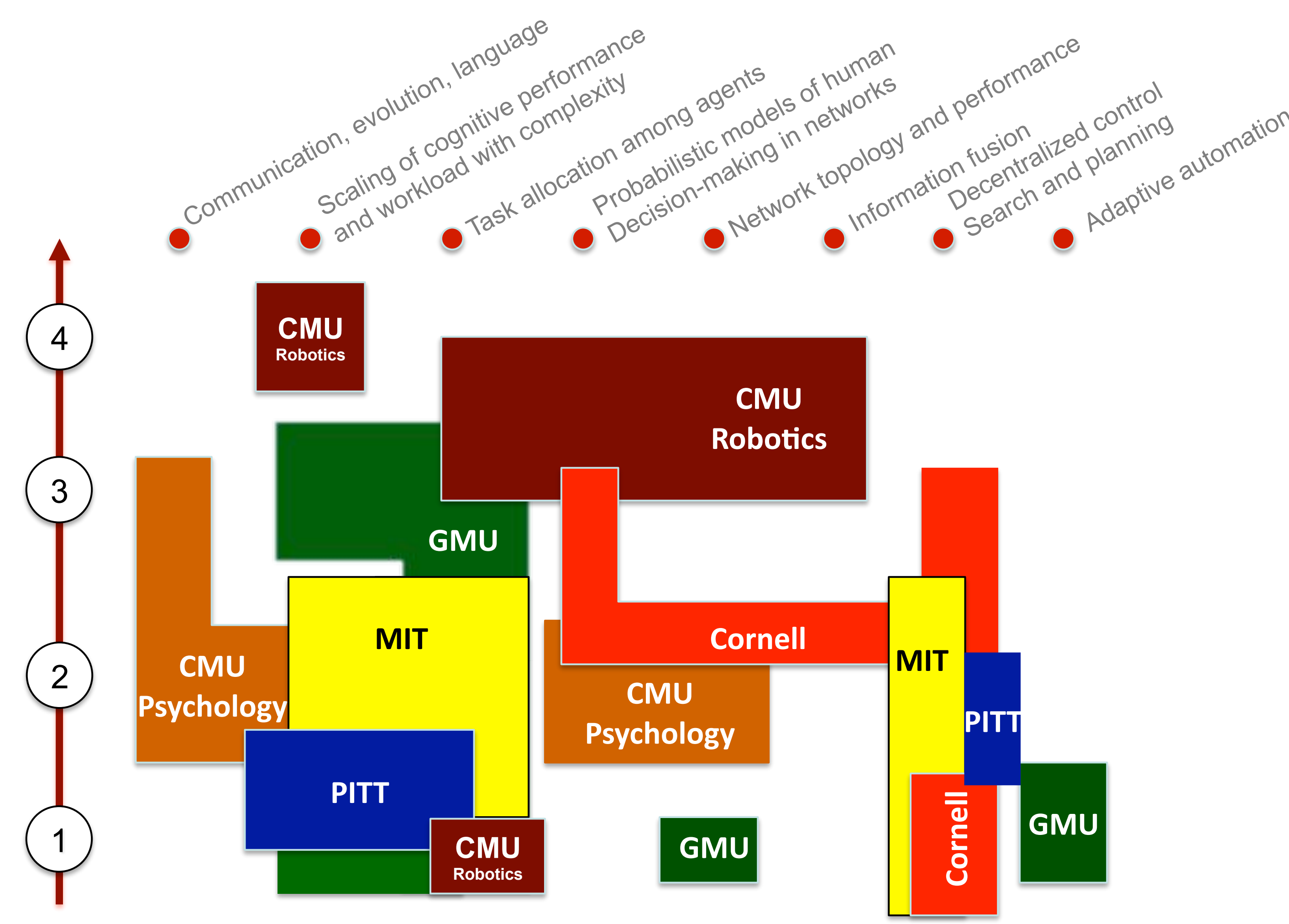




- Slider and over-ride provide statistically faster ID
- Over-ride provide slight improvement in mean
- Results on-going

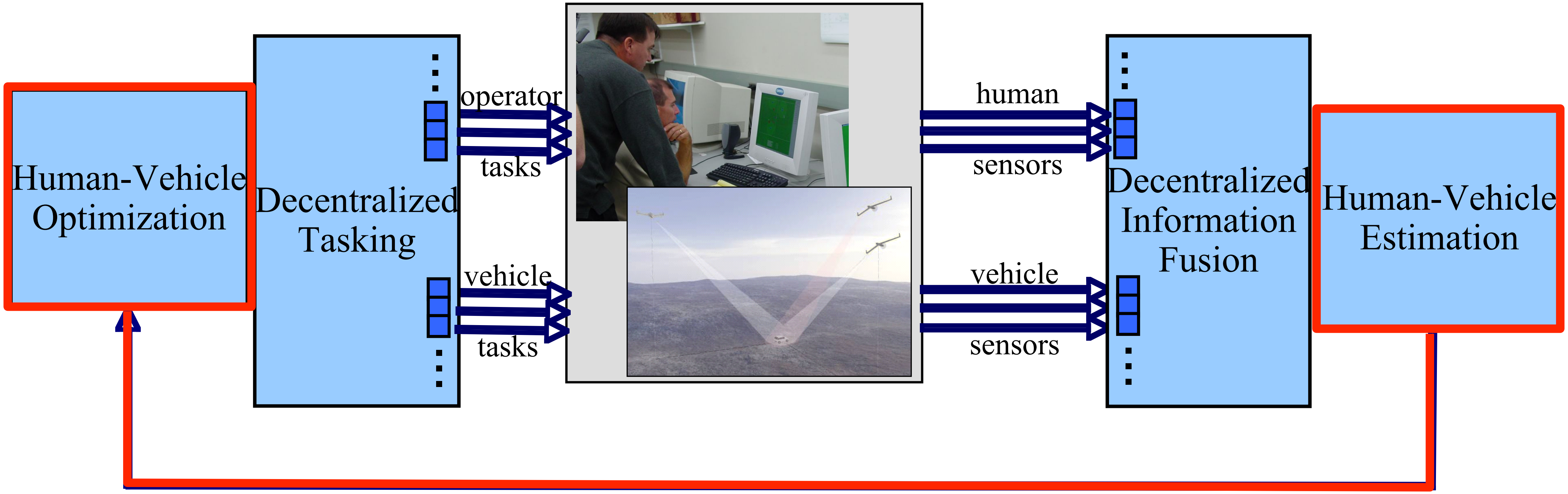
Future Work

- Modeling: Strategic (temporal)
  - Level 2
- Inference: More in-depth theory and analysis
  - Levels 2,3
- Network performance as a function of Scaling
  - Levels 2,3
- Collaborations
  - GMU: Adaptive Tasking (Level 1,2)
  - MIT: Decentralized Plan/Fusion (Level 1,2)



Collaborations: GMU

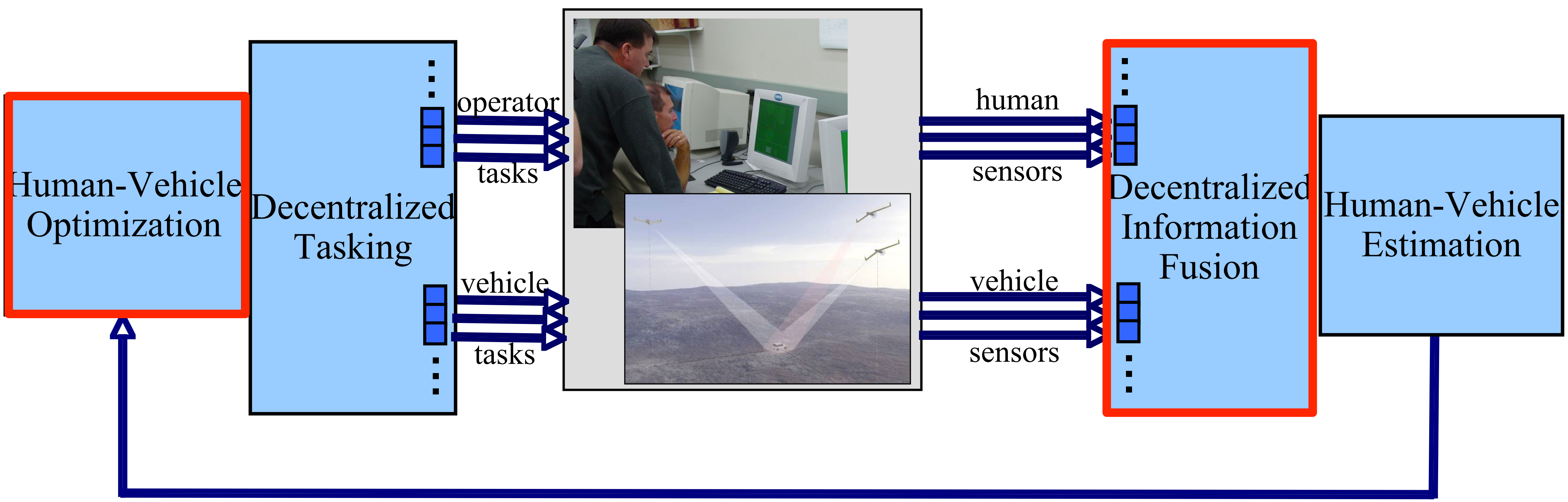
- Project #1: Models of current studies to develop deeper insight into correlations (e.g. scaling)



- Project #2: On-line performance inference, adaptive tasking

Collaborations: MIT

- Scaling to larger, more complex architectures
  - Local and remote agents
- Modeling: event driven, and decision modeling
- Integrated, Model based Fusion and Task Allocation:



Publications

- M. Campbell, "Intelligent Robotics in Sensor Network Applications," Keynote, SPIE Europe Conference on Unmanned Sensors and Sensor Networks, 2009.
- J. Schoenberg, M. Campbell, "Distributed Terrain Estimation Using a Mixture-Model Based Algorithm," 12th International Conference on Information Fusion, 2009.
- D. Shah, S. Galster, M. Campbell, F. Bourgault, N. Ahmed, B. Knott, "A Study of Human-Robotic Teams with Various Levels of Autonomy," 2009 AIAA Infotech conference.
- F. Bourgault, A. Chokshi, J. Wang, D. Shah, F. Cedano and M. Campbell, "Scalable Bayesian Human-Robot Cooperation in Mobile Sensor Networks," 2008 IEEE IROS.

- N. Ahmed, M. Campbell, "Variational Bayesian Data Fusion of Multi-class Discrete Observations in Cooperative Human-Robot Estimation," submitted to the 2010 ICRA.
- D. Lee, J. Schoenberg, M. Campbell, "An Empirical Study of Adaptive Tasking in Human-Robotic Search," submitted to the 2010 ICRA Conference
- N. Ahmed, M. Campbell, "Discriminative Subclass Modeling without Relabeling," submitted to the IEEE Transactions on Pattern Recognition.
- D. Shah, S. Galster, M. Campbell, N. Ahmed, B. Knott, "A Study of Human-Robotic Teams with Various Levels of Autonomy," submitted to the IEEE Transactions on Systems, Man and Cybernetics