To Ask or Not to Ask: A Foundation for the Optimization of Human-Robot Collaborations

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Outline

- Human-Robot Collaboration
- When to ask human for help
  - Math understanding of extent of human capability
  - Implication for field operation
    - Sensing, path planning and decision making
- Optimizing human-robot collaboration in target classification
  - Sensing, human help, energy usage
  - Understanding underlying patterns
- Optimizing human-robot collaboration in surveillance
  - Path planning, sensing, human help, energy usage
- Conclusions

Human-Robot Networks

- Humans:
  - Can solve complex problems
  - Valuable units
  - Limited time
- Robots:
  - Can go to places hard for human
  - Cost per unit less
- How to best optimize the interaction?

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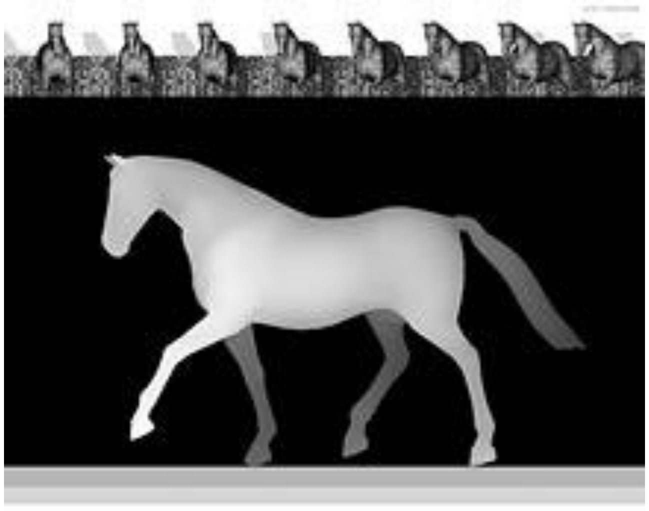

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To Ask or Not to Ask

- Humans can do complex visual tasks
- Visual recognition with missing info, noise, coarse resolution
- Far from modeling how humans do it
- Robot only needs to assess extent of human visual performance
- How can the robots best optimize cooperation based on this?

Should I ask, get more information, or use my own judgment?

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- Providing robots with a new understanding of human visual performance
- Profound implications for field decision making, sensing, navigation and communication

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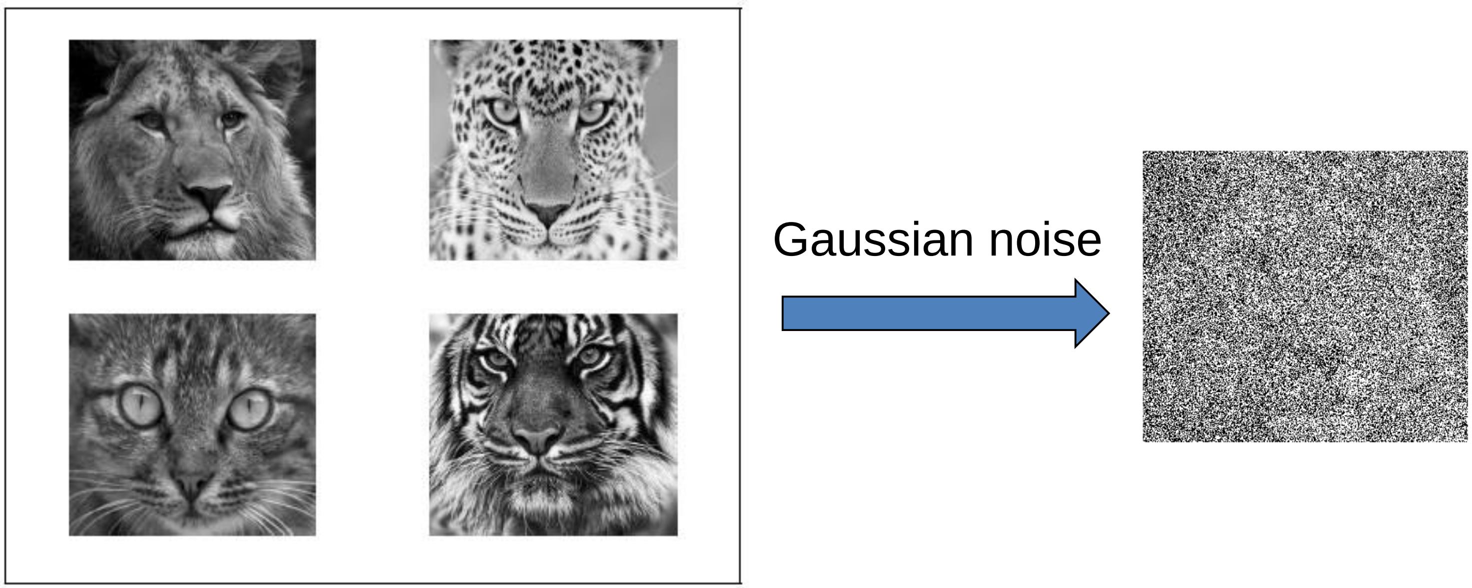
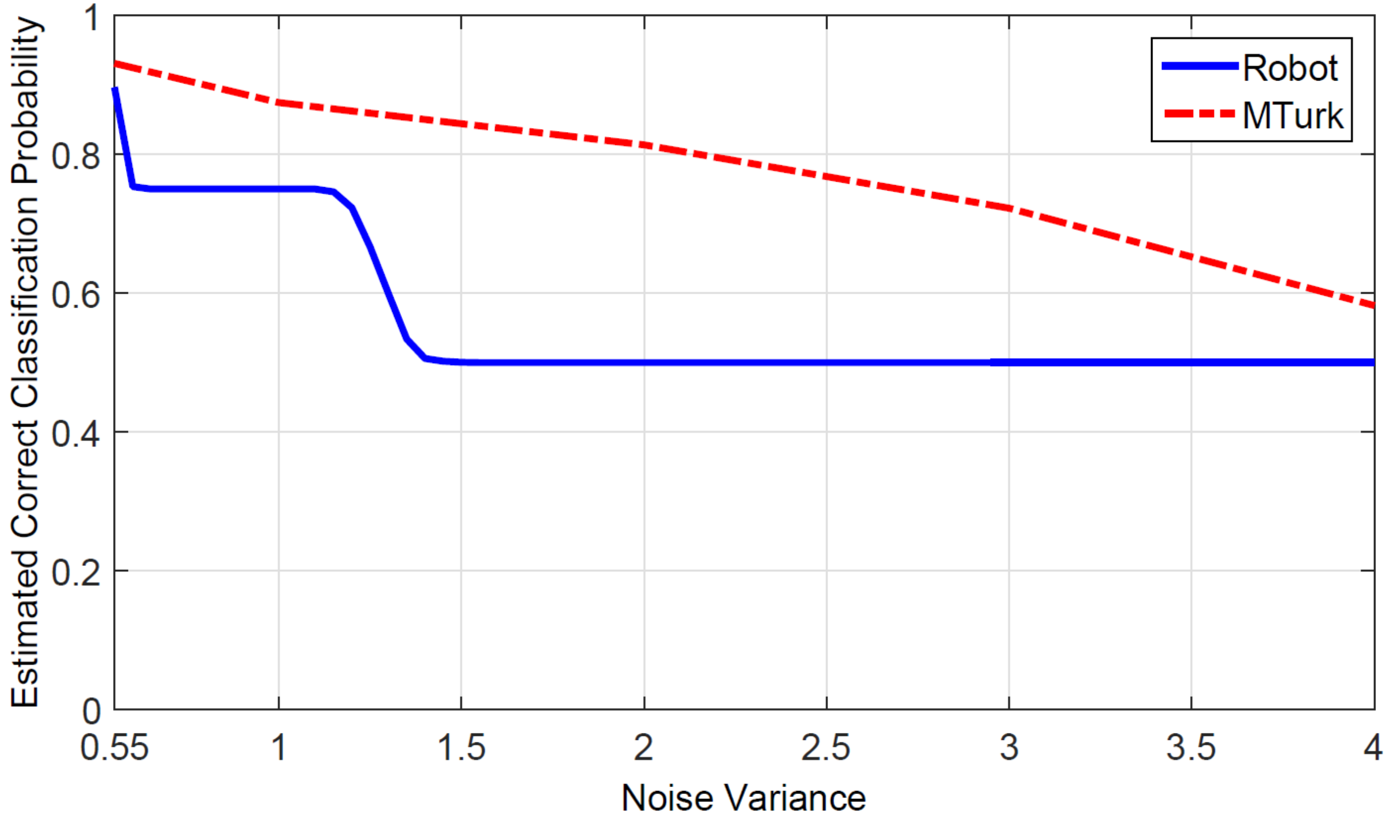
Understanding Human Visual Performance

- Target classification in the presence of noise
- Need human and robot correct classification probabilities



Performance Curves

- Human: Amazon Mechanical Turk (MTurk)
- Robot: Minimum distance detector



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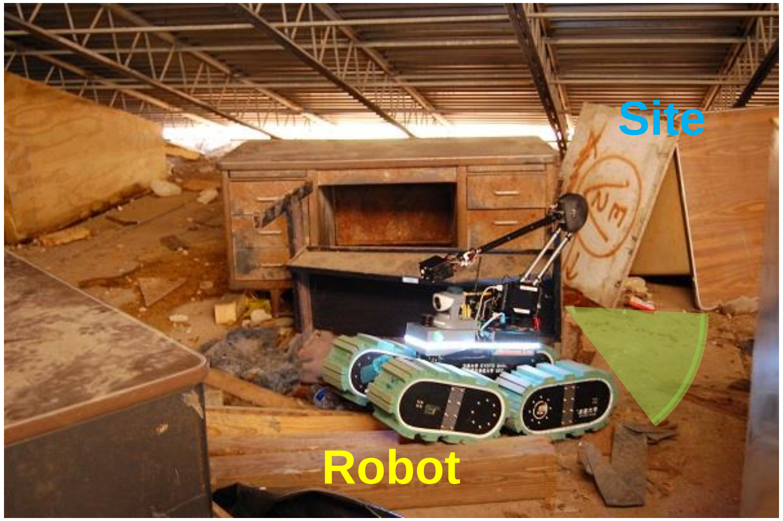
Collaborative Target Classification

- N sites, M available inquiries to human
- Human and robot correct classification probabilities (p_h and p_r)
- E_{max} total motion energy to visit all sites
  - Predefined routes to sites
  - E_k: motion energy to visit site k
  - High correct classification probability ($\tilde{p}$) for visited sites



Original image courtesy of IEEE Spectrum

Collaborative Target Classification

- Maximizing probability of correct classification under constraints

$$\max_{\gamma,\eta}.\quad \gamma^T(p_h - p_r) + \eta^T(\tilde{p}\mathbf{1} - p_r)$$

Gain from asking human   Gain from site visit

$$\text{s.t.}\quad \eta^T\mathscr{E} \le \mathscr{E}_{\max}, \quad \mathbf{1}^T\gamma \le M$$

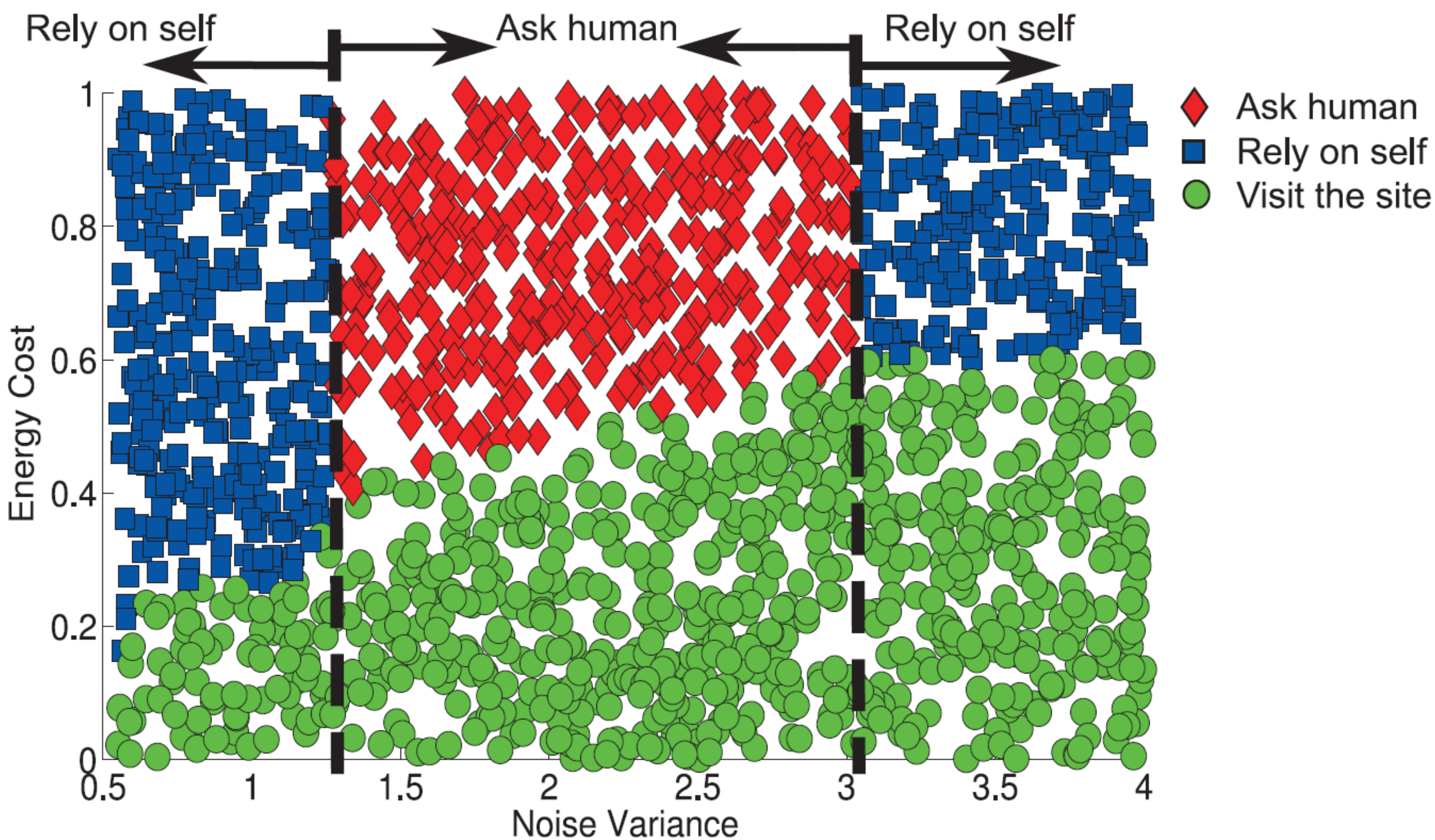
Motion energy constraint   Total queries allowed

$$\gamma, \eta, \gamma + \eta \in \{0,1\}^N$$

Ask or not ask   Visit or not visit

Emerging Underlying Pattern

- 2000 sites, 500 questions, 25% energy



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Emerging Underlying Pattern (cont.)

- Relaxing binary constraints
- Karush-Kuhn-Tucker (KKT) conditions
- Lemma: Let $\eta^\star$ and $\gamma^\star$ denote optimum decision vectors for two sites k and l.
  - 1) If $\gamma_k^\star = 1,\ \eta_k^\star = 0,\ \gamma_l^\star = 0$ and $\eta_l^\star = 0$,
    then $p_{h,k} - p_{r,k} \geq p_{h,l} - p_{r,l}$ ← Greater benefit from asking human
  - 2) If $\gamma_k^\star = 0,\ \eta_k^\star = 1,\ \gamma_l^\star = 0$ and $\eta_l^\star = 0$,
    then $\frac{\tilde{p} - p_{r,k}}{E_k} \geq \frac{\tilde{p} - p_{r,l}}{E_l}$ ← Higher gain normalized by energy cost

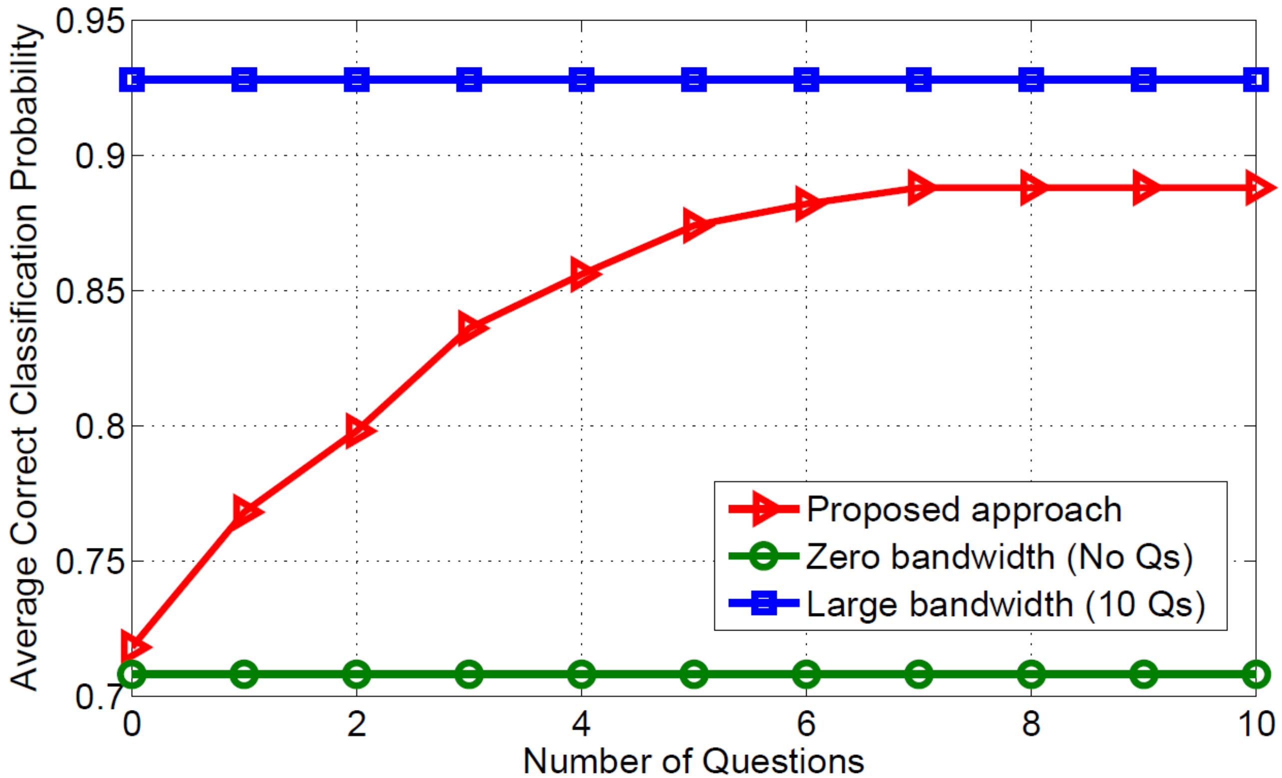
Energy Saving

- 10 sites, 4 allowed questions
- Baseline: no knowledge of human performance

Target Ave. Correct Classification Prob.	**% Energy Saving**
0.7	66.67%
0.75	44.30%
0.8	27.83%
0.85	6.3%
0.9	0.71%
0.915	Inf

Bandwidth Saving

- 10 sites, 30% energy
  - Near optimal performance (4.3% worse) with 40% less BW usage



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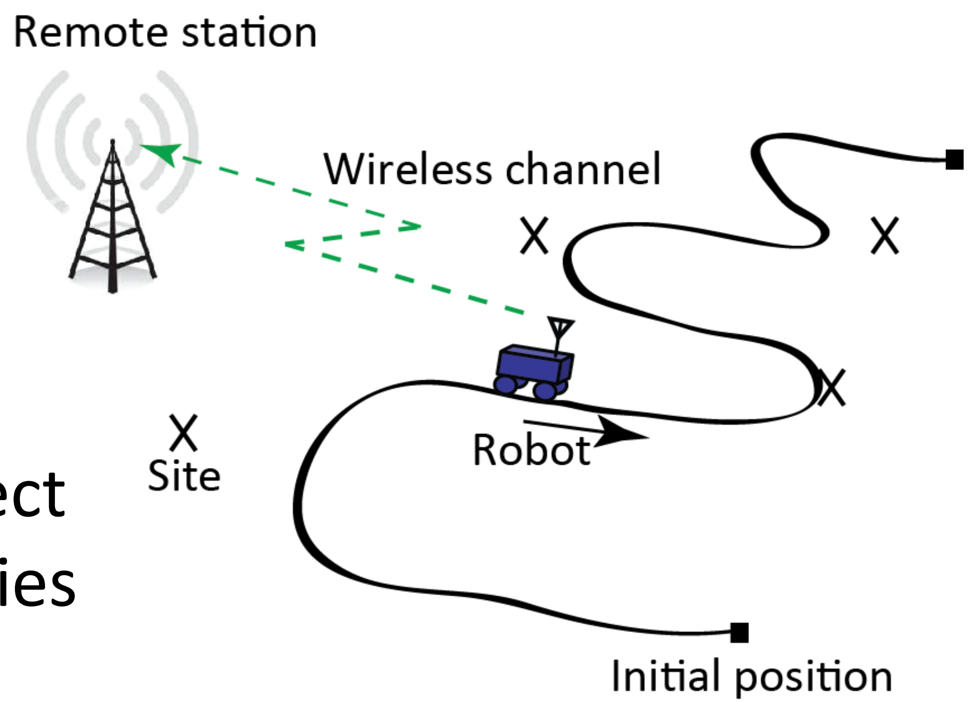
Bandwidth Saving (cont.)

- 10 sites, 30% energy
- Baseline: no knowledge of human performance

Target Ave. Correct Classification Prob.	% Bandwidth Saving
0.7	37.04%
0.75	48.61%
0.8	33.18%
0.85	7.33%
0.875	Inf

Collaborative Surveillance

- Optimization of path planning, sensing and communication
- N sites, M available inquiries to human
- Human and robot correct classification probabilities as functions of sensing distance
- E_{max} total motion energy
  - No predefine routes



Path Planning and Query Optimization

- Problem Formulation

$$
\begin{aligned}
\max_{x,\gamma}.\quad & \frac{1}{N}\Big(\sum_{k=1}^{N}(1-\gamma_k)\max_{x_i}\ p_{r,k}(x_i)+\gamma_k\max_{x_i}\ p_{h,k}(x_i)\Big)\\
\text{s.t.}\quad & \sum_{k=1}^{N}\gamma_k \le M, \quad \mathscr{E}(x)\le \mathscr{E}_{\max},\\
& ||x_k - x_{k+1}||_2 \le \delta_r, \quad \forall k = 1,2,\ldots,x_{\text{num}}-1,\\
& \gamma_k \in \{0,1\}, \quad \forall k = 1,2,\ldots,N,
\end{aligned}
$$

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Path Planning and Query Optimization

- Problem Formulation

$$\max_{x,\gamma} \quad \frac{1}{N}\left(\sum_{k=1}^{N}(1-\gamma_k)\max_{x_i}\ p_{r,k}(x_i)+\gamma_k\max_{x_i}\ p_{h,k}(x_i)\right)$$

Trajectory

Best robot performance

Best human performance

$$\text{s.t.} \quad \sum_{k=1}^{N}\gamma_k \le M, \quad \mathscr{E}(x) \le \mathscr{E}_{\max}$$

Total queries allowed

Motion energy budget

$$||x_k - x_{k+1}||_2 \le \delta_r, \quad \forall k = 1,2,\ldots,x_{\text{num}}-1$$

Speed limit

$$\gamma_k \in \{0,1\}, \quad \forall k = 1,2,\ldots,N$$

Ask or not ask

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Path Planning and Query Optimization

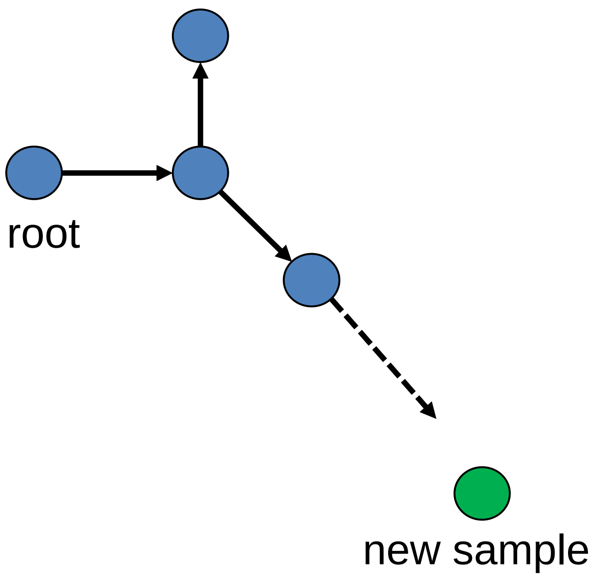
- Problem Formulation

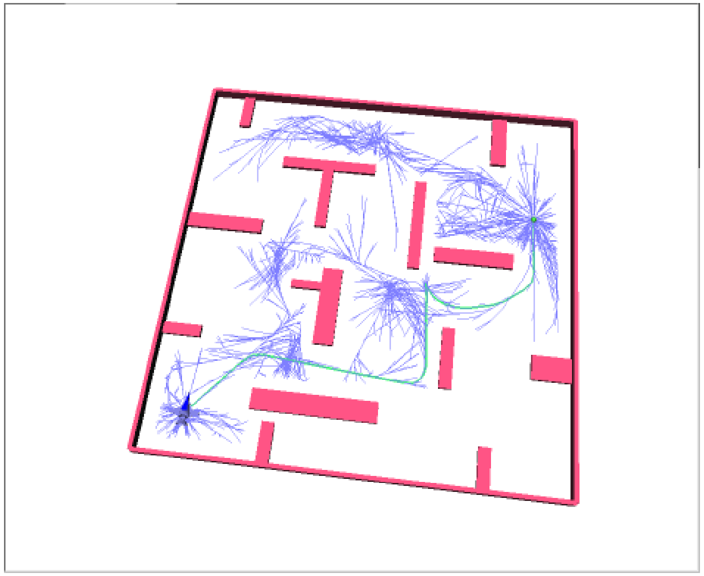
$$\begin{aligned} \max_{x,\gamma}. \quad & \frac{1}{N}\Big(\sum_{k=1}^{N}(1-\gamma_k)\max_{x_i}\; p_{r,k}(x_i)+\gamma_k\max_{x_i}\; p_{h,k}(x_i)\Big) \\ \text{s.t.} \quad & \sum_{k=1}^{N}\gamma_k \le M, \quad \mathscr{E}(x) \le \mathscr{E}_{\max}, \\ & ||x_k - x_{k+1}||_2 \le \delta_r, \quad \forall k = 1,2,\ldots,x_{\text{num}}-1, \\ & \gamma_k \in \{0,1\}, \quad \forall k = 1,2,\ldots,N, \end{aligned}$$

Challenging to solve due to binary constraints and route design

Rapidly Exploring Random Tree Star (RRT*)

- Sampling-based motion planning algorithm
  - Proposed by Karaman et al.
- Fast and efficient
- Can easily embed our binary constraints





LaValle, http://msl.cs.uiuc.edu/rrt/gallery_2drot.html

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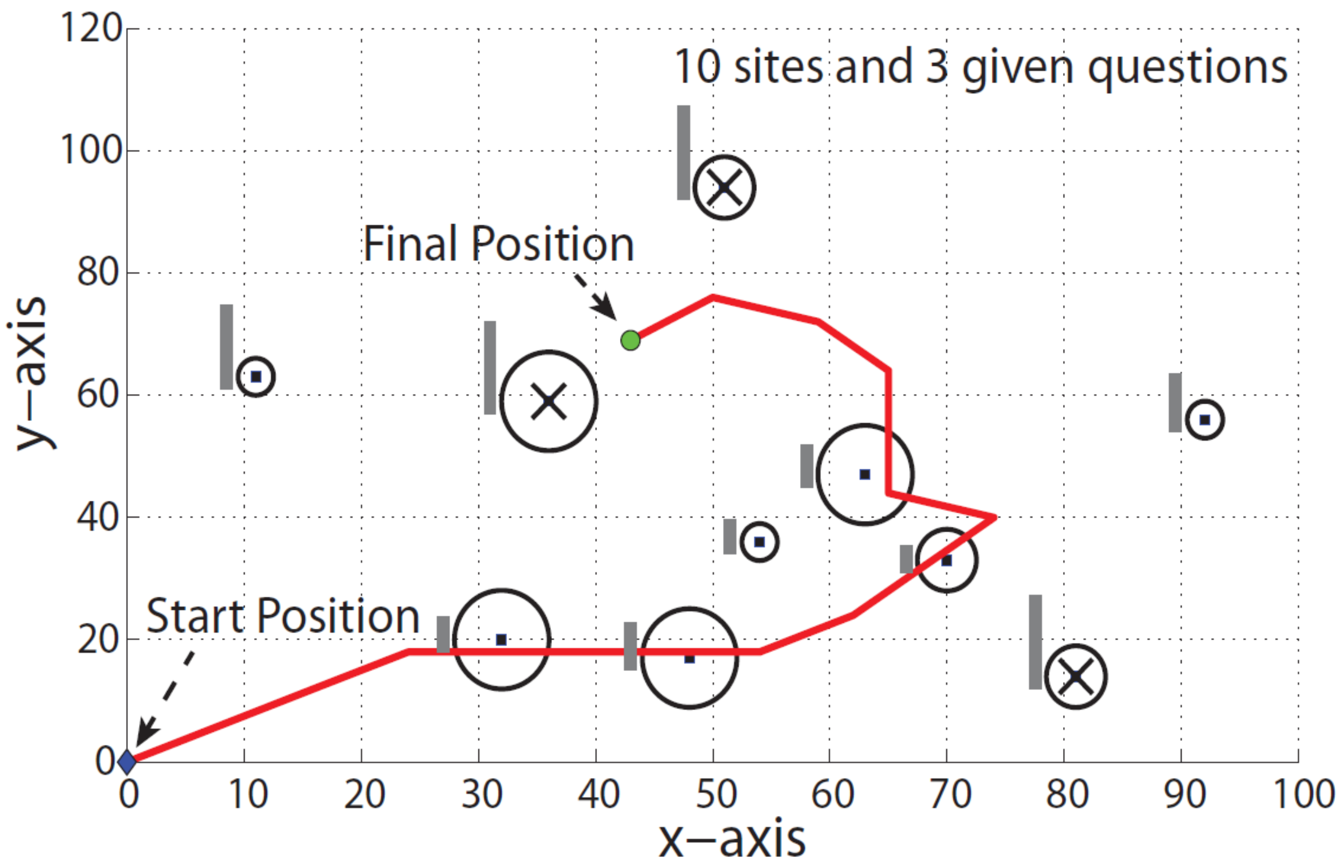
Modified RRT*

- Motion energy budget as a constraint on the total length of the path
- Select/update which sites to ask at each end node
  - Ask the M sites with largest difference between best human and best robot performance
  - $\max_{x_i} p_{h,k}(x_i) - \max_{x_j} p_{r,k}(x_j)$
  - Can prove that this is the optimal thing to do
- Evaluate objective function at each end node

Collaborative Surveillance



Circle size: sensing difficulty

Cross: ask human

Bar: performance gain from asking human

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Energy Saving

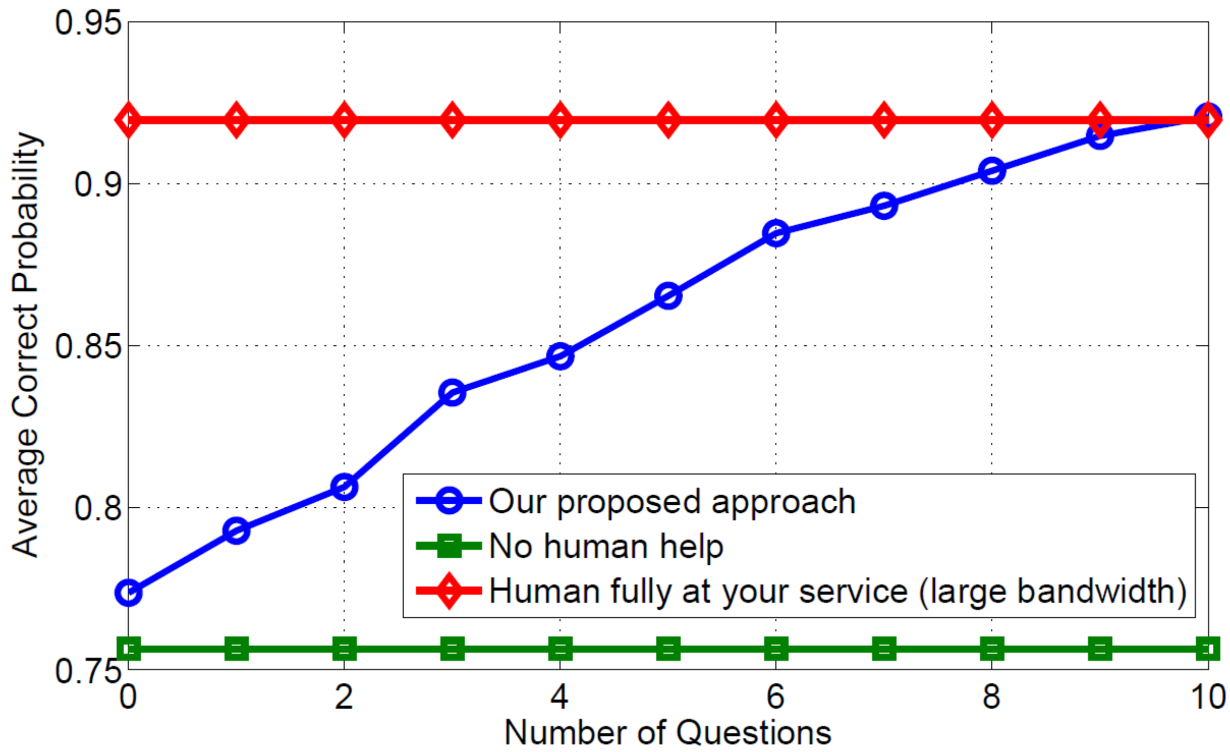
- Compared to not asking questions

# of Queries	% Energy Saving as Compared to No Collaboration
2	44.96%
5	69.39%
10	93.99%

  - Target correct classification probability 0.8
  - Can save energy considerably even with a small number of questions
    - ➢45% energy reduction with 2 questions

Bandwidth Saving

- 10 sites, 6 allowed questions
  - Near optimal performance (3.8% worse) with 40% less BW usage



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Conclusions

- Human Robot Collaborations
- How to combine strengths of both
- Understanding extent of human visual performance
- Implication for robotic field operation
- To Ask or Not to Ask problem
  - When to ask for human help
  - When to rely on own judgement
  - When to incur motion energy and sense more
- Target classification and field surveillance
  - Underlying patterns
  - Energy and bandwidth saving

Thank you!

This work was supported in part by NSF NeTS award # 1321171.