A Human-Robot Collaborative Traveling Salesman Problem:

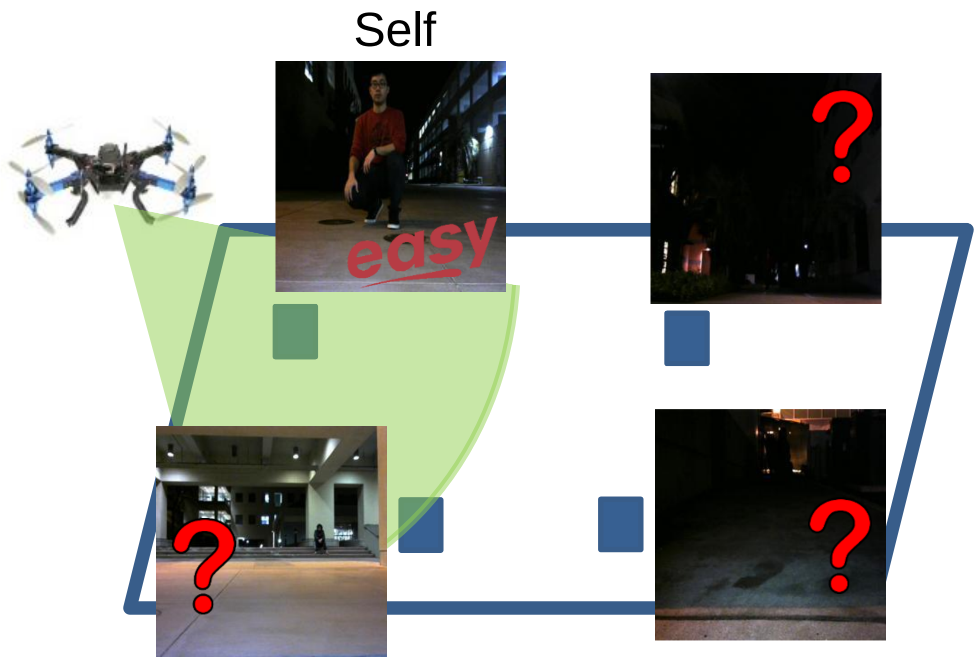
Robotic Site Inspection with Human Assistance

Hong (Herbert) Cai and Yasamin Mostofi

Department of Electrical and Computer Engineering

University of California Santa Barbara

Collaborative Surveillance Task: Asking for Help



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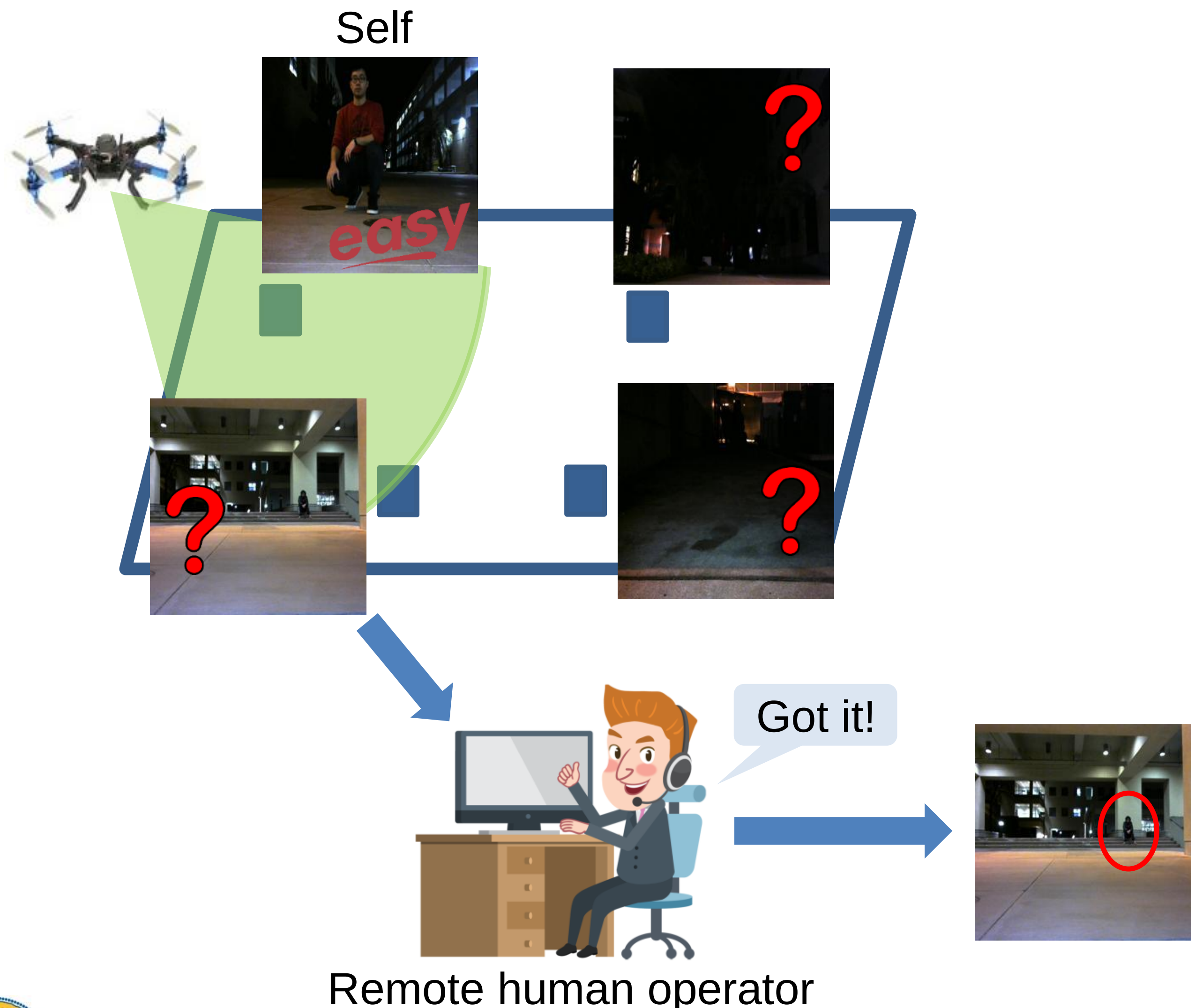

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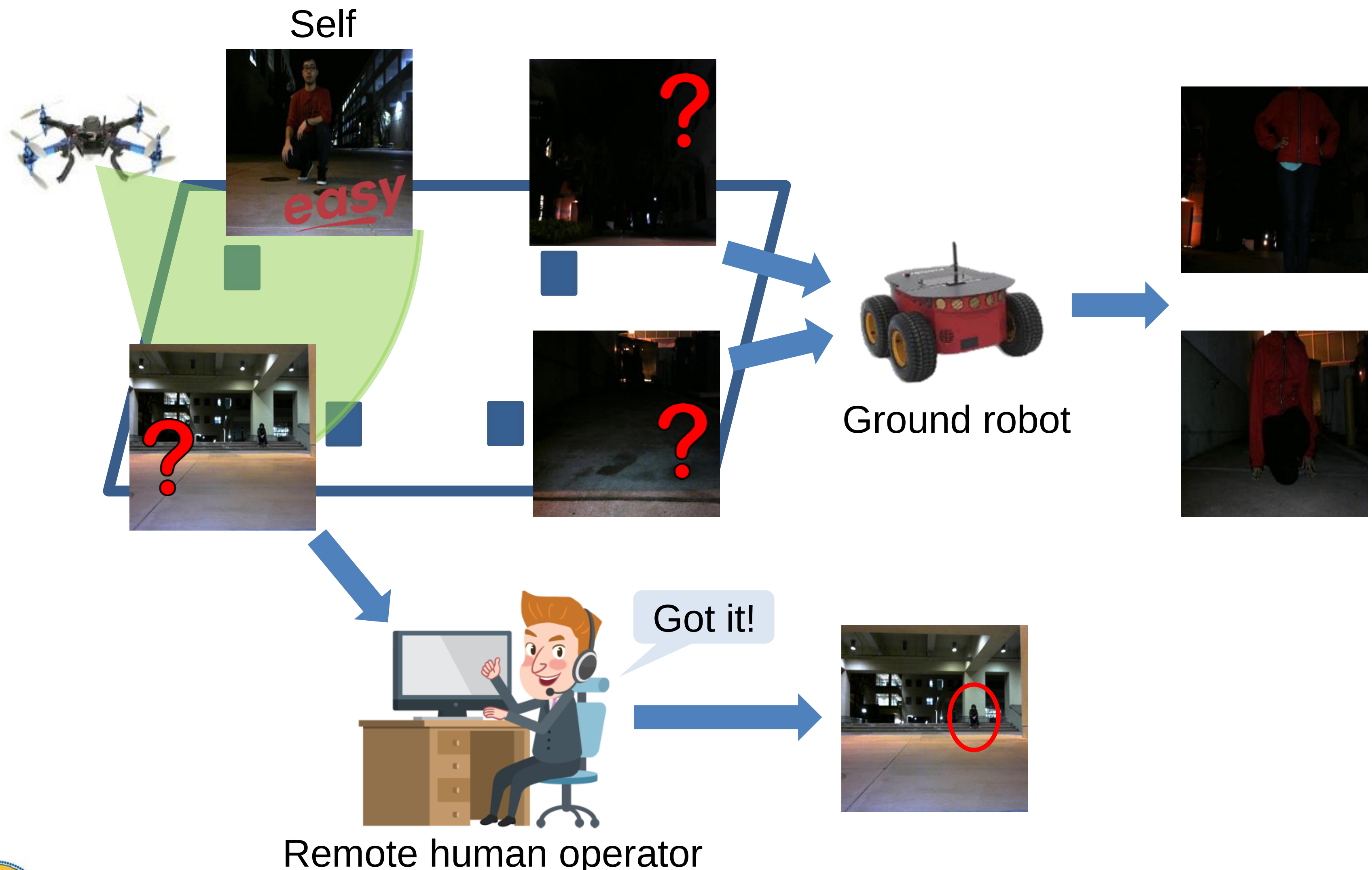
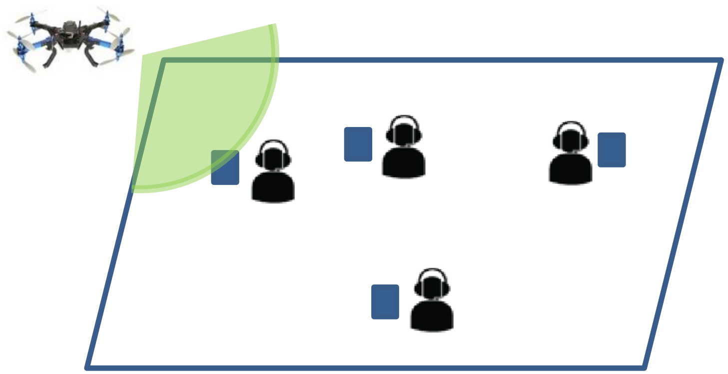


How to Properly Ask for Help - Implications for Field Decision Making



- Performance may not be good
- Too much workload

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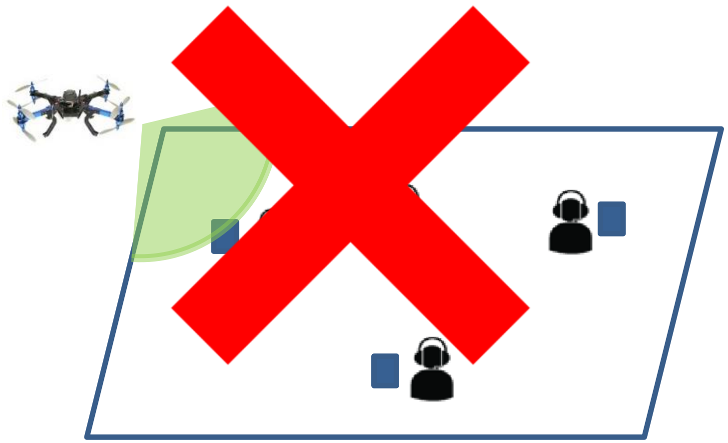

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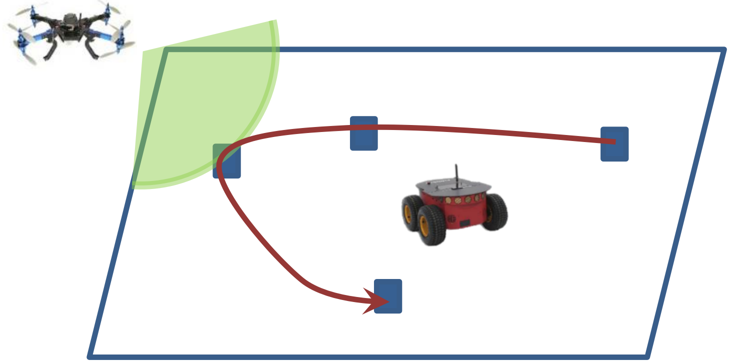

- Energy consuming

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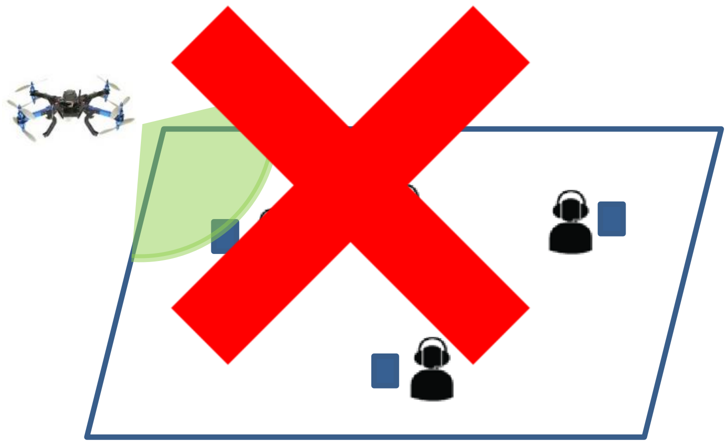

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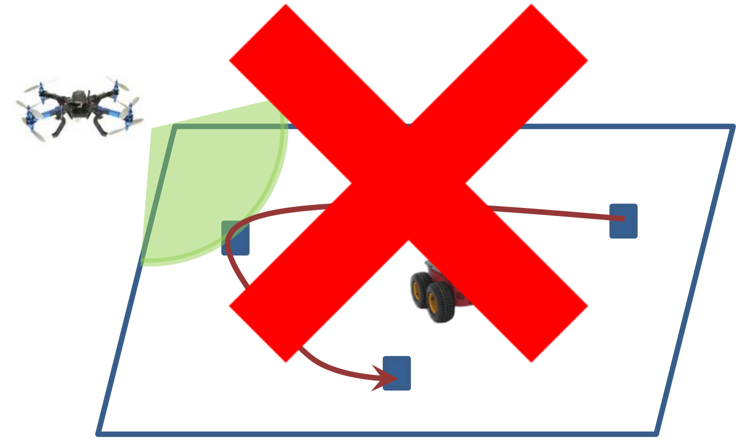

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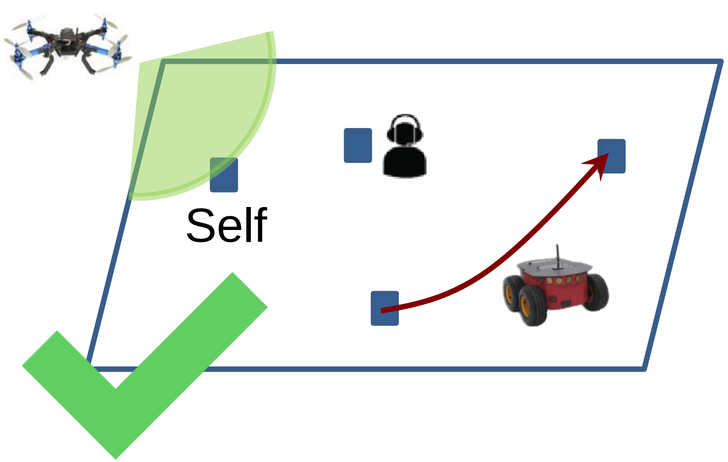
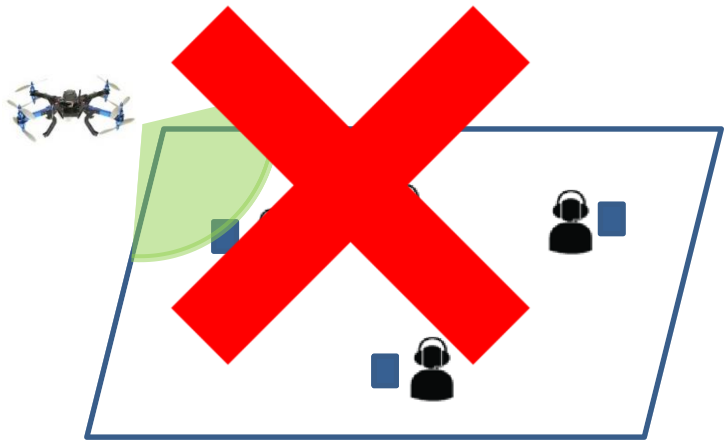


- Select the right sites to ask for help from remote human operator
- Select the right sites to ask for closer inspection

How to Properly Ask for Help - Implications for Field Decision Making



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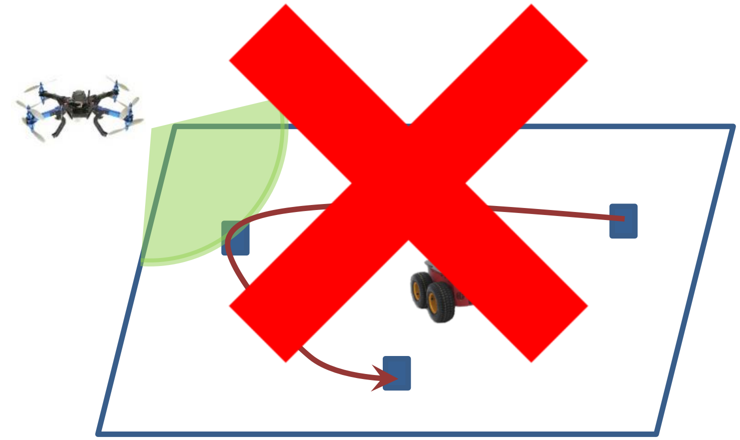

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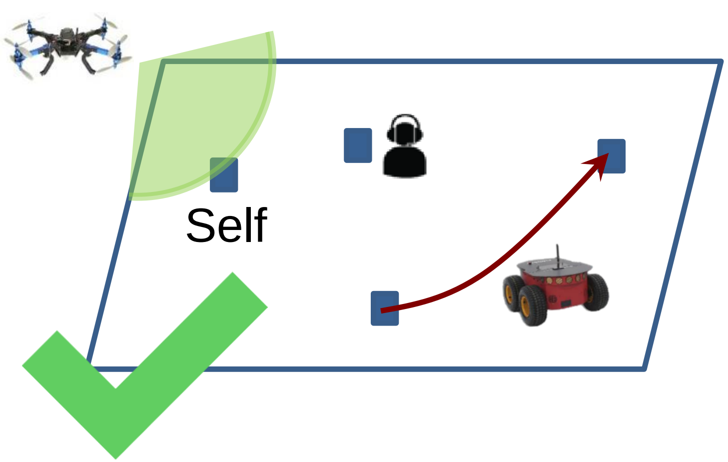
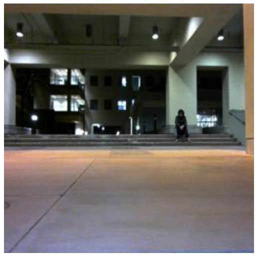


- Robot needs to predict human visual performance given a visual input



Easy

Hard

Outline

- Human-Robot Collaborative Traveling Salesman Problem under Energy Constraints
- Summary of Predicting Human Visual Performance
  - Using image quality metrics
  - Using machine learning
- Co-optimization of Tour Design and Human Collaboration
- Probabilistic Performance Characterization
- Conclusions

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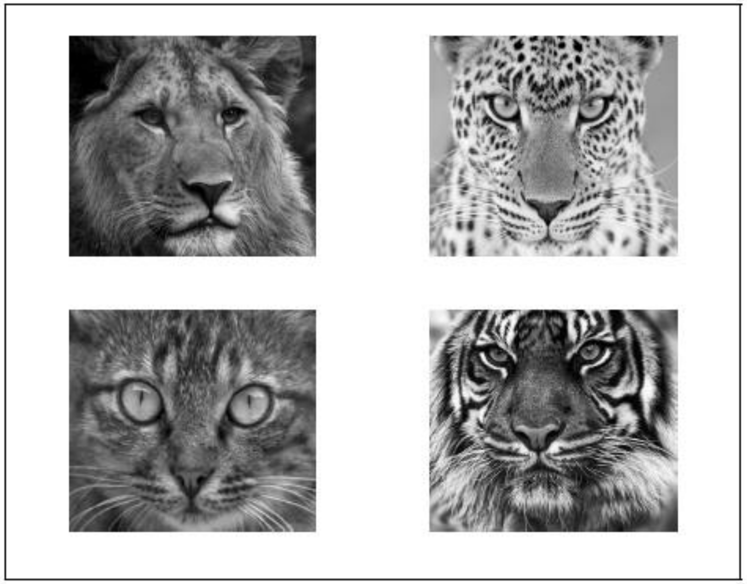
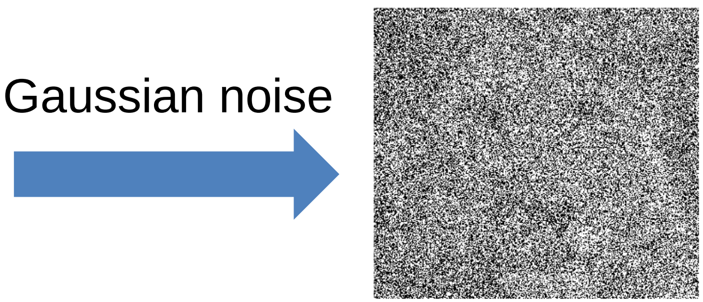
Predicting Human Visual Performance Using Image Quality Metrics

- Identify one or more image quality metrics that are strongly related to human performance
- Object classification under additive noise

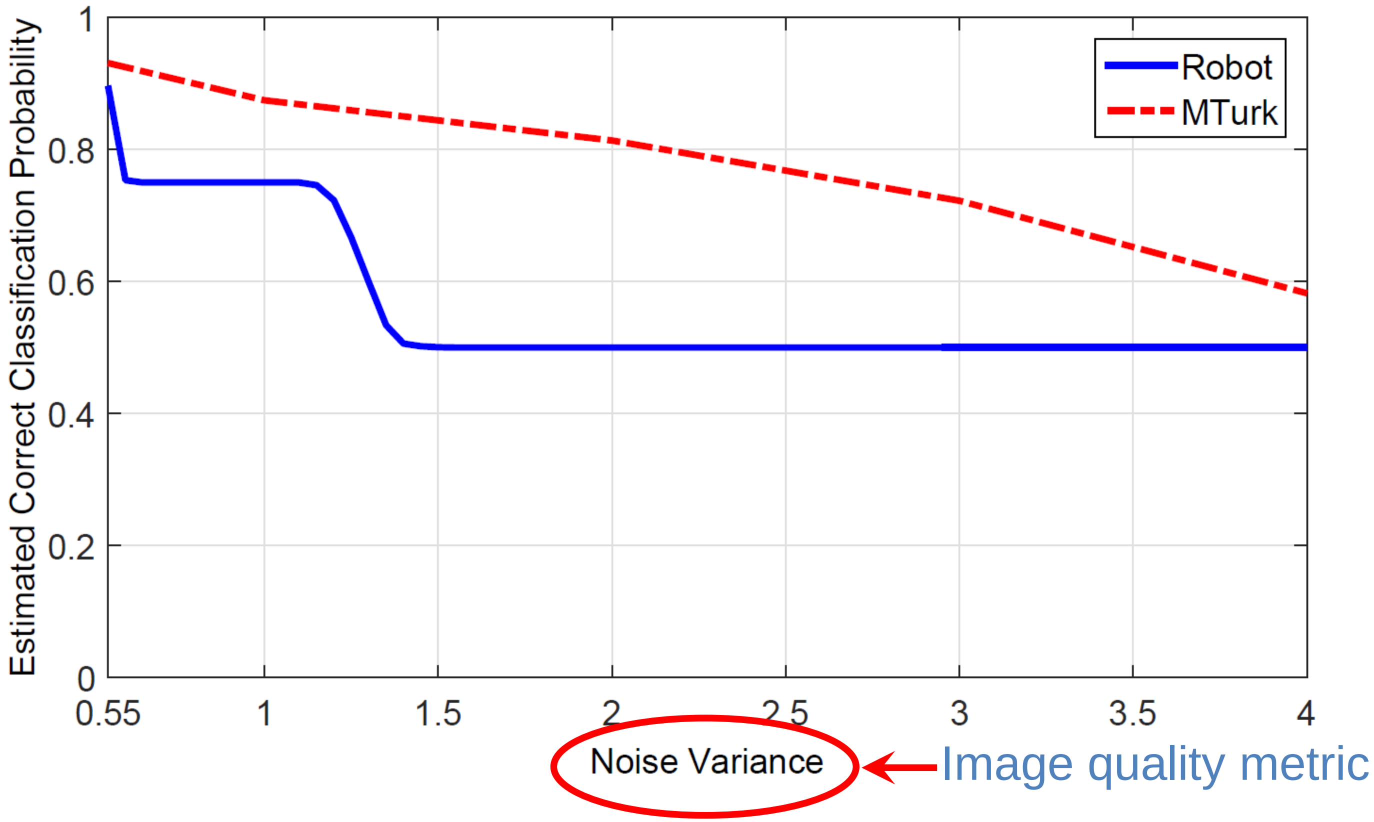




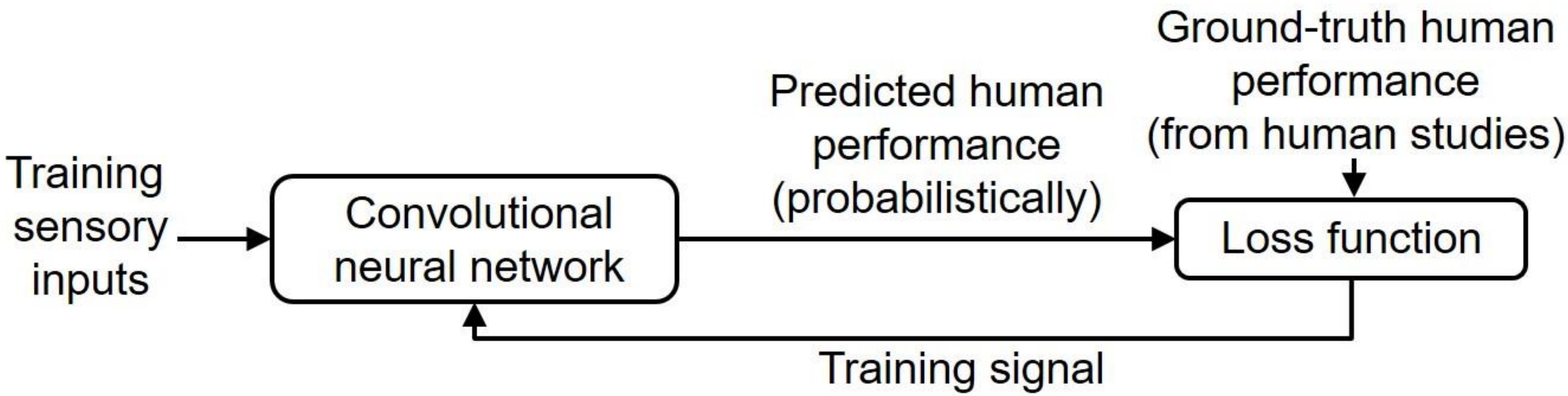
H. Cai and Y. Mostofi, “To Ask or Not to Ask: A Foundation for the Optimization of Human-Robot Collaborations”, American Control Conference (ACC), 2015

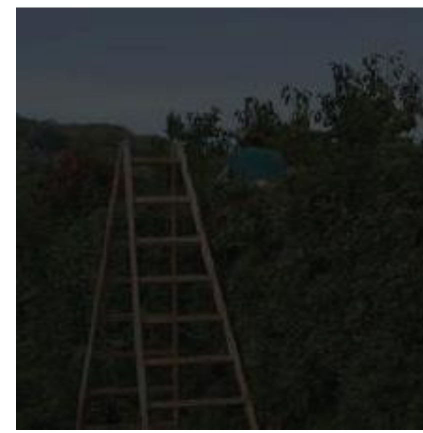
Performance Curves under Additive Noise

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



Predicting Human Visual Performance Using Machine Learning



			
True prob.: 1 Pred. prob.: 1	True prob.: 0.87 Pred. prob.: 0.88	True prob.: 1 Pred. prob.: 1	True prob.: 0.76 Pred. prob.: 0.79

H. Cai and Y. Mostofi, "Asking for Help with the Right Question by Predicting Human Visual Performance", Robotics: Science and Systems (RSS), 2016

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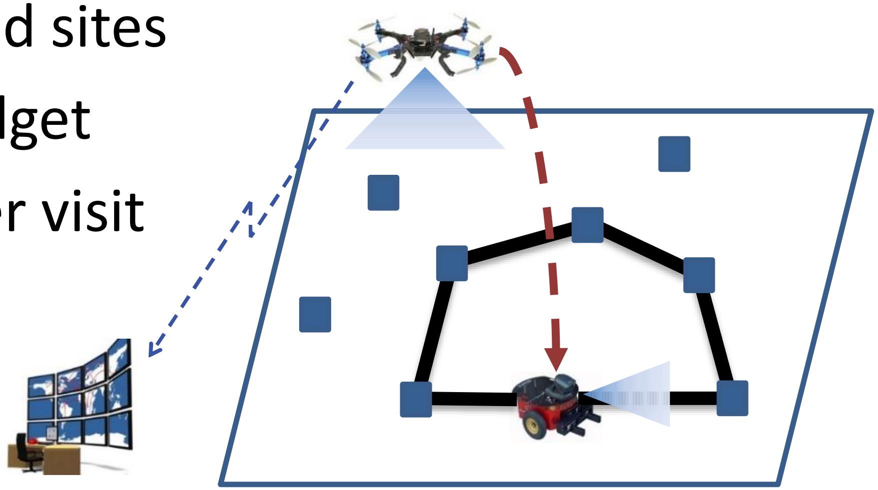
Co-Optimization of Tour Design and Human Collaboration

- UAV conducts initial sensing by taking images of sites
  - Predicts human and robot performance (p_h and p_r)
- UAV needs to select sites to query human operator
  - Limited number of allowed questions
- UAV needs to select sites for further inspection by ground vehicle
  - Forms a tour of the selected sites
  - Limited motion energy budget
  - Good performance ($\tilde{p}$) after visit



Optimizing Sensing, Navigation and Collaboration

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

Perf. gain from site visit

Perf. gain from asking human

Ask

Visit

$$\text{s.t.} \quad (1)\ \kappa \sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} z_{i,j} d_{i,j} \leq \mathscr{E},$$

Motion energy budget

A visited site should only be entered and exited once

$$(2)\ \sum_{j=1, i\neq j}^{N} z_{i,j} = \sum_{j=1, i\neq j}^{N} z_{j,i} = \eta_i,\ \forall i = 1, \ldots, N,$$

$$(3)\ u_i - u_j + 1 \leq (N-1)(1 - z_{i,j}),\ \forall i,j = 2, \ldots, N,$$

$$(4)\ 2 \leq u_i \leq |V|,\ \forall i = 2, \ldots, N,$$

MTZ constraints for sub-tour elimination

$$(5)\ \mathbf{1}^T\gamma \leq M, \quad (6)\ \gamma + \eta \preceq \mathbf{1},$$

M total queries allowed

Total number of sites

$$(7)\ \gamma, \eta \in \{0,1\}^N,\ z \in \{0,1\}^{N\times(N-1)},\ u \in \{0,1\}^{N-1}$$

Optimizing Sensing, Navigation and Collaboration

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

$$\text{s.t.} \quad (1)\ \kappa \sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} z_{i,j} d_{i,j} \leq \mathscr{E},$$

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$$(4)\ 2 \leq u_i \leq |V|, \ \forall i = 2, \ldots, N,$$

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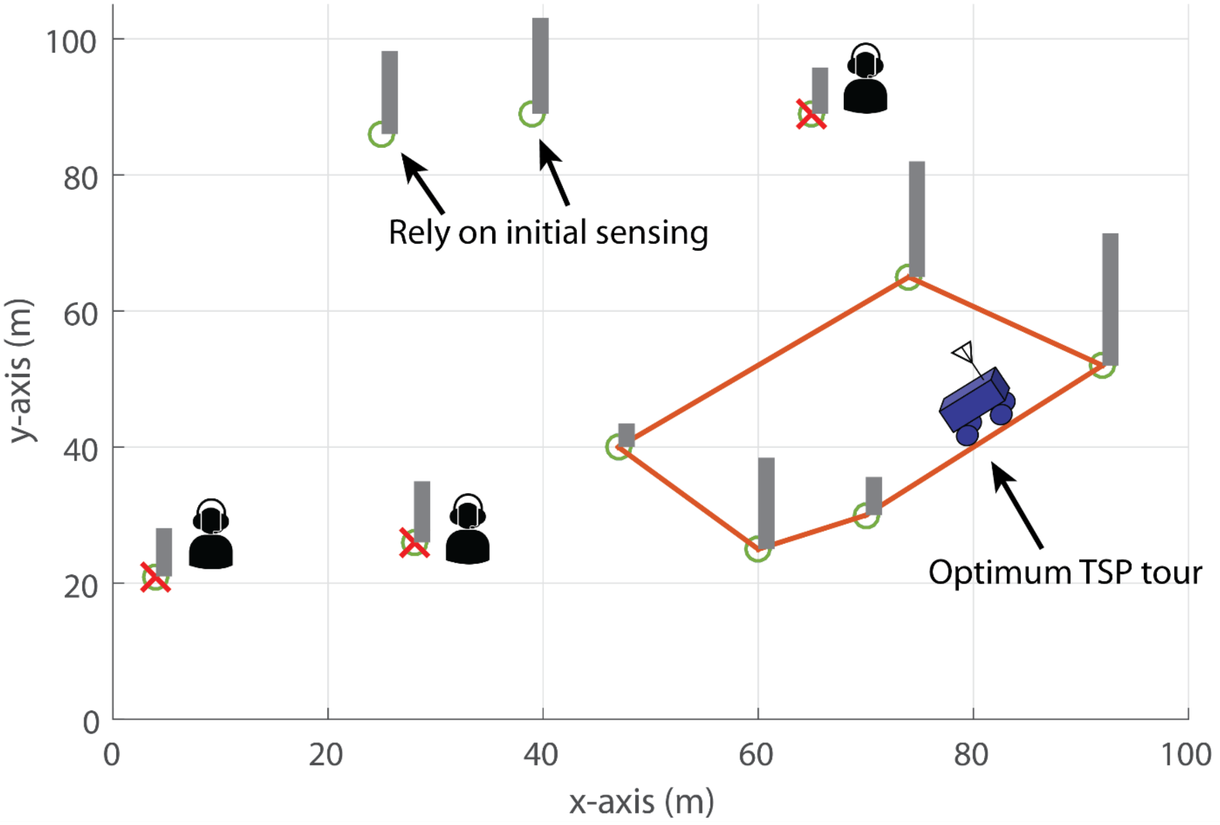
$$(7)\ \gamma, \eta \in \{0,1\}^N, \ z \in \{0,1\}^{N\times(N-1)}, \ u \in \{0,1\}^{N-1}$$

Coupling between tour design and human collaboration

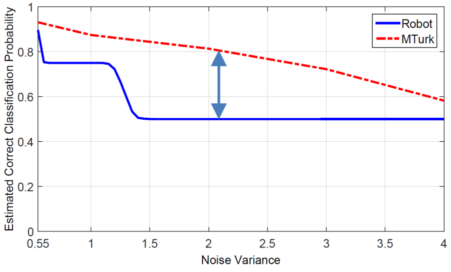
- Proposition: Let $\eta^\star$ and $\gamma^\star$ denote optimum decision vectors for two sites i and j. If $\gamma_i^\star = 1,\ \eta_i^\star = 0,\ \gamma_j^\star = 0$ and $\eta_j^\star = 0$, then $p_{h,i} - p_{r,i} \geq p_{h,j} - p_{r,j}$.

Greater benefit from asking human

Sample Simulation Result



Bar: initial sensing variance



Energy Saving

- 15 sites, 6 allowed questions
  - Benchmark: No knowledge of human performance
    - ➢ Maximizes sum of sensing variances of visited sites
    - ➢ Randomly queries human with remaining sites

Desired Ave. Correct Classification Prob.	Ave. % Energy Saving
0.7	57.69%
0.75	28.00%
0.8	13.16%
0.85	3.85%
0.9	Inf

  - Also large savings in communication bandwidth usage

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Predicting Collaborative Performance Based on Given Resources

- Predicting performance based on given resources
  - Motion energy budget: $E = \alpha E_N$
    - E_N : minimum required motion energy to tour all sites and $\alpha \in [0,1]$
  - M allowed queries to human operator
- Assumption:
  - Average edge length is the same in the *N*-site TSP tour and the energy constrained TSP tour (with selected sites)
    - Valid if number of sites large and α not too small

Case of No Communication

- Lemma 1

  Expected correct classification probability approximated by

$$E[p_c|M=0] \approx \frac{1}{N}(\alpha N\tilde{p} + (N-\alpha N)\bar{p}_r)$$

  - $\bar{p}_r$: expected robot correct classification probability

Proof:
$$\begin{aligned}
\mathbb{E}[p_c|M=0] &= \frac{1}{N}(\mathbb{E}[\sum_{i=1}^{N}\eta_i(\tilde{p}-p_{r,i})] + \mathbb{E}[\sum_{i=1}^{N}p_{r,i}]),\\
&= \frac{1}{N}(\mathbb{E}_{N_v}[\mathbb{E}[\sum_{i=1}^{N}\eta_i(\tilde{p}-p_{r,i})|N_v]] + \mathbb{E}[\sum_{i=1}^{N}p_{r,i}]),\\
&= \frac{1}{N}(\mathbb{E}[N_v(\tilde{p}-\bar{p}_r)] + N\bar{p}_r),\\
&= \frac{1}{N}(\mathbb{E}[N_v]\tilde{p} + (N-\mathbb{E}[N_v])\bar{p}_r),\\
&\approx \frac{1}{N}(\alpha N\tilde{p} + (N-\alpha N)\bar{p}_r),
\end{aligned}$$

Number of sites visited

$\bar{p}_r$ assumed for both visited/unvisited sites

$E[N_v] \approx \alpha N$
Valid when N large and α not too small

Case of Zero Motion Energy Budget

- Lemma 2

  Expected correct classification probability can be approximated by

$$E[p_c|\alpha = 0] \approx \frac{1}{N}(M\bar{p}_h + (N - M)\bar{p}_r)$$

- $\bar{p}_h$: expected human correct classification probability
- $\bar{p}_r$: expected robot correct classification probability
- Assumptions:
  - $\bar{p}_h$ assumed for queried sites
  - $\bar{p}_r$ assumed for both queried and unqueried sites

Prediction Based on Motion Energy Budget and Queries to the Human Operator

- Theorem 1

Expected correct classification probability approximated by

$$E[p_c] \approx \frac{1}{N}\left(\alpha N\tilde{p} + p_{nv}(\alpha N)\right)$$

$N_h = \min\{N - N_v, M\}$

$N_r = N - N_v - N_h$

Proof: $E[p_c] = \frac{1}{N}\left(E_{N_v}[N_v\tilde{p} + N_h\bar{p}_h + N_r\bar{p}_r]\right)$

Visit Ask Self

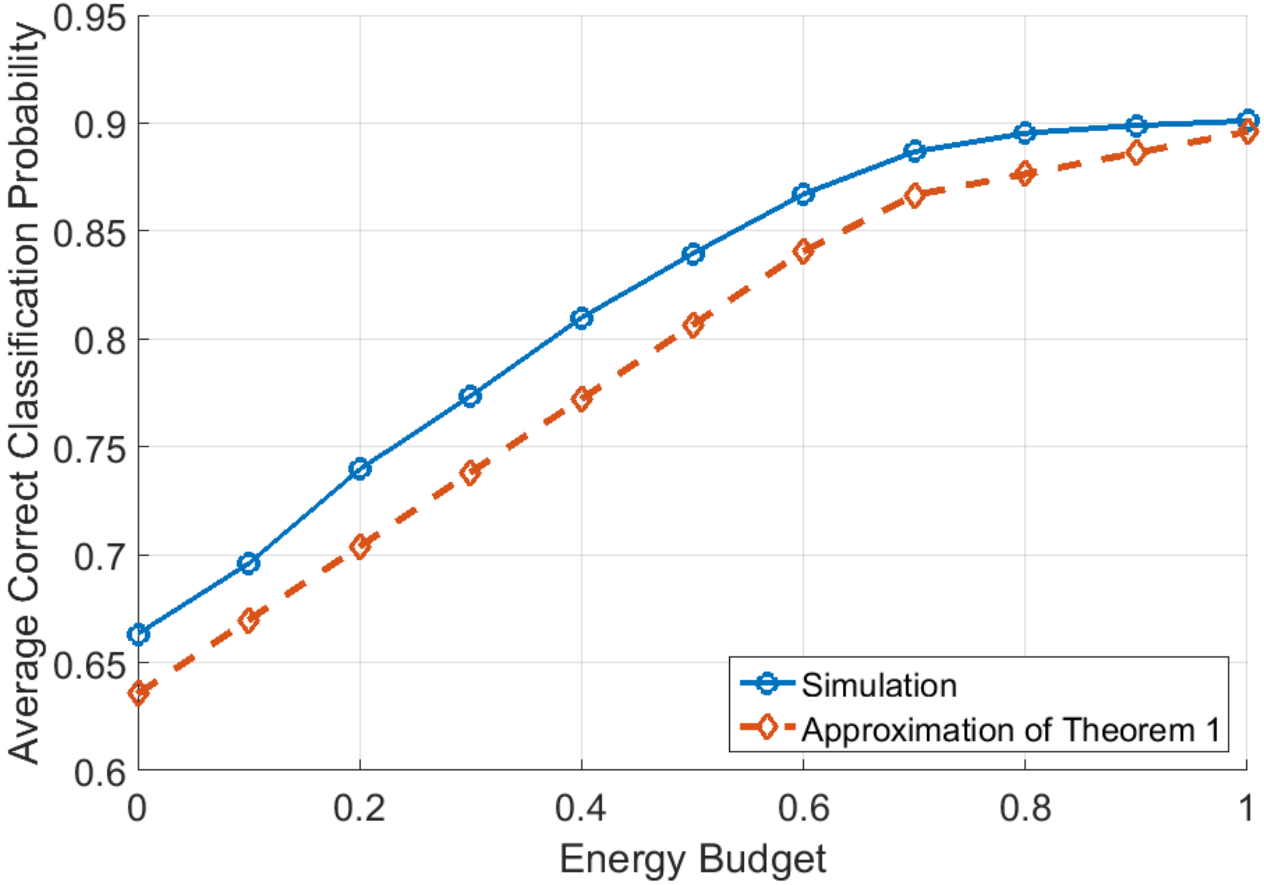
$$= \frac{1}{N}\left(E[N_v]\tilde{p} + E[\underbrace{p_{nv}(N_v)}_{N_h\bar{p}_h + N_r\bar{p}_r}]\right)$$

Approx. error upper- bounded by $(\bar{p}_h - \bar{p}_r)/4$ $\rightarrow$ $\approx \frac{1}{N}\left(E[N_v]\tilde{p} + p_{nv}(E[N_v])\right)$

$E[N_v] \approx \alpha N$ $\rightarrow$ $\approx \frac{1}{N}\left(\alpha N\tilde{p} + p_{nv}(\alpha N)\right)$

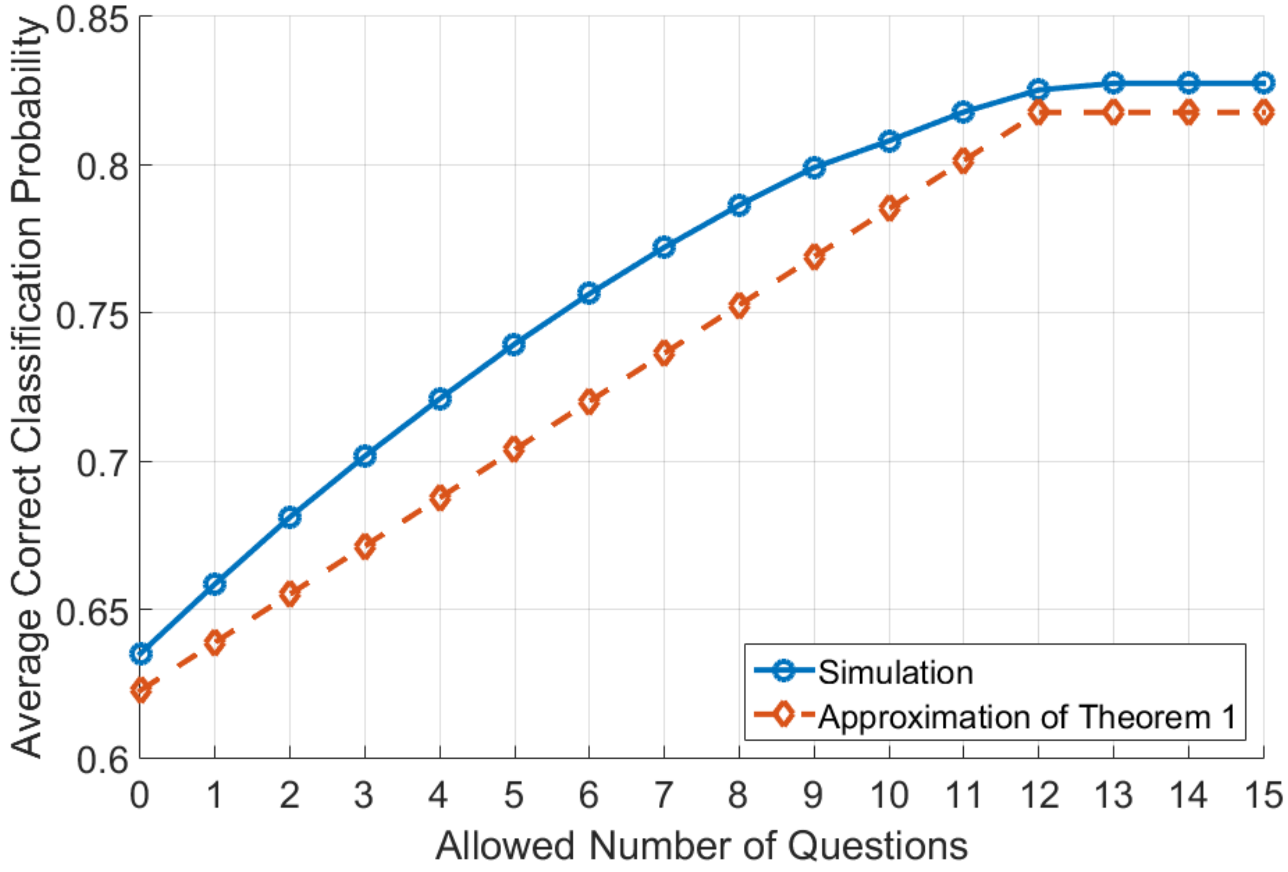
Prediction vs. Numerical Result

- 15 sites, 5 allowed queries



Prediction vs. Numerical Result

- 15 sites, energy budget α = 0.2



Conclusions

- Collaborative surveillance task
  – Select the right sites to ask for further inspection and help from remote human operator
- Predict human visual performance
  – Prediction using image quality metrics
  – Prediction using machine learning
- Co-optimization of tour design and human collaboration
  – Utilize human performance prediction
  – Significantly outperforms benchmark
- Mathematical performance characterization
  – Predict performance based on given resources

Thank you!

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

Prediction vs. Numerical Result

- 15 sites, 5 allowed queries