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?

Original image courtesy of US Navy

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Human-Robot Networks

• Humans:
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• Robots:
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• How to best optimize the interaction?
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?
To Ask or Not to Ask: A Foundation for the Optimization of Human-Robot Collaboration

• 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

Gaussian noise
Performance Curves

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

\[
\max_{\gamma, \eta} \quad \gamma^T (p_h - p_r) + \eta^T (\tilde{p}1 - p_r)
\]

- Gain from asking human
- Gain from site visit

\[
\text{s.t.} \quad \eta^T \mathcal{E} \leq \mathcal{E}_{\text{max}}, \quad 1^T \gamma \leq M
\]

- Motion energy constraint
- Total queries allowed

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

- Ask or not ask
- Visit or not visit

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Emerging Underlying Pattern

- 2000 sites, 500 questions, 25% energy
Emerging Underlying Pattern (cont.)

- Relaxing binary constraints
- Karush-Kuhn-Tucker (KKT) conditions
- Lemma: Let $\eta^*$ and $\gamma^*$ denote optimum decision vectors for two sites $k$ and $l$.
  
  1) If $\gamma^*_k = 1$, $\eta^*_k = 0$, $\gamma^*_l = 0$ and $\eta^*_l = 0$,
  
  then $p_{h,k} - p_{r,k} \geq p_{h,l} - p_{r,l}$ \textbf{Greater benefit from asking human}

  2) If $\gamma^*_k = 0$, $\eta^*_k = 1$, $\gamma^*_l = 0$ and $\eta^*_l = 0$,
  
  then $\frac{\bar{p} - p_{r,k}}{E_k} \geq \frac{\bar{p} - p_{r,l}}{E_l}$ \textbf{Higher gain normalized by energy cost}
Energy Saving

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

<table>
<thead>
<tr>
<th>Target Ave. Correct Classification Prob.</th>
<th>% Energy Saving</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>66.67%</td>
</tr>
<tr>
<td>0.75</td>
<td>44.30%</td>
</tr>
<tr>
<td>0.8</td>
<td>27.83%</td>
</tr>
<tr>
<td>0.85</td>
<td>6.3%</td>
</tr>
<tr>
<td>0.9</td>
<td>0.71%</td>
</tr>
<tr>
<td>0.915</td>
<td>Inf</td>
</tr>
</tbody>
</table>
Bandwidth Saving

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

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

<table>
<thead>
<tr>
<th>Target Ave. Correct Classification Prob.</th>
<th>% Bandwidth Saving</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7</td>
<td>37.04%</td>
</tr>
<tr>
<td>0.75</td>
<td>48.61%</td>
</tr>
<tr>
<td>0.8</td>
<td>33.18%</td>
</tr>
<tr>
<td>0.85</td>
<td>7.33%</td>
</tr>
<tr>
<td>0.875</td>
<td>Inf</td>
</tr>
</tbody>
</table>
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
- \( E_{\text{max}} \) total motion energy
  - No predefine routes
Path Planning and Query Optimization

• Problem Formulation

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

s.t. \[\sum_{k=1}^{N} \gamma_k \leq M, \quad \mathcal{E}(x) \leq \mathcal{E}_{\text{max}},\]

\[\|x_k - x_{k+1}\|_2 \leq \delta_r, \quad \forall k = 1, 2, ..., x_{\text{num}} - 1,\]

\[\gamma_k \in \{0, 1\}, \quad \forall k = 1, 2, ..., N,\]
Path Planning and Query Optimization

• Problem Formulation

\[
\begin{align*}
\text{max.} & \quad \frac{1}{N} \left( \sum_{k=1}^{N} (1 - \gamma_k) \max_{x_i} p_{r,k}(x_i) + \gamma_k \max_{x_i} p_{h,k}(x_i) \right) \\
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\end{align*}
\]

- Trajectory
- Best robot performance
- Best human performance
- Total queries allowed
- Motion energy budget
- Speed limit
- Ask or not ask

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Path Planning and Query Optimization

• Problem Formulation

\[
\begin{align*}
\text{max. } & \quad \frac{1}{N} \left( \sum_{k=1}^{N} (1 - \gamma_k) \max_{x_i} p_{r,k}(x_i) + \gamma_k \max_{x_i} p_{h,k}(x_i) \right) \\
\text{s.t. } & \quad \sum_{k=1}^{N} \gamma_k \leq M, \quad \mathcal{E}(x) \leq \mathcal{E}_{\text{max}}, \\
& \quad \|x_k - x_{k+1}\|_2 \leq \delta_r, \quad \forall k = 1, 2, \ldots, x_{\text{num}} - 1, \\
& \quad \gamma_k \in \{0, 1\}, \quad \forall k = 1, 2, \ldots, N,
\end{align*}
\]

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

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

Final Position
Start Position

10 sites and 3 given questions
Energy Saving

• Compared to not asking questions

<table>
<thead>
<tr>
<th># of Queries</th>
<th>% Energy Saving as Compared to No Collaboration</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>44.96%</td>
</tr>
<tr>
<td>5</td>
<td>69.39%</td>
</tr>
<tr>
<td>10</td>
<td>93.99%</td>
</tr>
</tbody>
</table>

– 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
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!

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