Enhancing Human Capability with Intelligent Machine Teammates

Julie Shah
Associate Professor
Department of Aeronautics and Astronautics
Computer Science and Artificial Intelligence Lab
Current State in Human-Robot Teaming

Amazon Robotics

BMW Spartanburg, SC
Current State in Human-Robot Teaming

- Coexistence but *not* Collaboration.
Inferring hidden mental states enables richer, flexible human-machine teaming

- Problem: Current models for HRI and teamwork are based on empirical observation – which works well for highly structured interaction.
Inferring hidden mental states enables richer, flexible human-machine teaming

• Problem: Current models for HRI and teamwork are based on empirical observation – which works well for highly structured interaction.

• Richer collaborations require inferring human mental state.
Inferring hidden mental states enables richer, flexible human-machine teaming

• Problem: Current models for HRI and teamwork are based on empirical observation — which works well for highly structured interaction.
• Richer collaborations require inferring human mental state.

Machine observables \(\Rightarrow\) Mental State
Inferring hidden mental states enables richer, flexible human-machine teaming

- Problem: Current models for HRI and teamwork are based on empirical observation — which works well for highly structured interaction.
- Richer collaborations require inferring human mental state.

Machine observables → Mental State

Well-established cognitive models

- Meaningful features that relate to mental state
- Model structure to process complex information efficiently
Inferring hidden mental states enables richer, flexible human-machine teaming

- Problem: Current models for HRI and teamwork are based on empirical observation – which works well for highly structured interaction.
- Richer collaborations require inferring human mental state.

Machine observables \(\rightarrow\) Mental State

Well-established cognitive models

Meaningful features that relate to mental state
Model structure to process complex information efficiently
Inferring hidden mental states enables richer, flexible human-machine teaming

- Problem: Current models for HRI and teamwork are based on empirical observation – which works well for highly structured interaction.
- Richer collaborations require inferring human mental state.

**Team Plan Formation**

- Pre-planning
- Do we have consensus?
- What have we agreed to?
- Apprenticeship
- What to do in this situation?

**Dynamic Plan Execution**
Inferring hidden mental states enables richer, flexible human-machine teaming

- [Hidden State] What is the current state of our commitment to each decision?

- [Hidden State] What is our teammate’s context for decision-making?

Machine observables $\Rightarrow$ Mental State

Well-established cognitive models

Meaningful features that relate to mental state

Model structure to process complex information efficiently
Inferring hidden mental states enables richer, flexible human-machine teaming

- [Hidden State] What is the current state of our commitment to each decision?  — Do we have consensus? What have we agreed to?

- [Hidden State] What is our teammate’s context for decision-making?

Machine observables ? Mental State

Well-established cognitive models

Meaningful features that relate to mental state
Model structure to process complex information efficiently
Inferring hidden mental states enables richer, flexible human-machine teaming

- [Hidden State] What is the current state of our commitment to each decision? — Do we have consensus? What have we agreed to?

- [Hidden State] What is our teammate’s context for decision-making? — What will we do next?

Machine observables  

Well-established cognitive models  

Mental State  

Meaningful features that relate to mental state  

Model structure to process complex information efficiently
Inferring hidden mental states enables richer, flexible human-machine teaming

- [Hidden State] What is the current state of our commitment to each decision? — Do we have consensus? What have we agreed to?

- [Hidden State] What is our teammate’s context for decision-making? — What will we do next?

Machine observables \( \rightarrow \) Mental State

Well-established cognitive models

Meaningful features that relate to mental state

Model structure to process complex information efficiently
Human-Machine Collaboration to Improve Consistency of Shared Understanding

Machine observables ➔ ? ➔ Mental State

Input: Topic Discussion
A: We should send UAV to upper region.
B: What’s the weather like up there?
.....
B: Okay, let’s do that

<table>
<thead>
<tr>
<th>Dialogue Acts</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Suggestion</td>
<td>Consistent</td>
</tr>
<tr>
<td>Question-Info</td>
<td>Inconsistent</td>
</tr>
<tr>
<td>Acceptance</td>
<td>“Could we review this topic once more?”</td>
</tr>
</tbody>
</table>

Predict
Human-Machine Collaboration to Improve Consistency of Shared Understanding

Question → Suggest → Accept → Confirm

Four patterns of dialog acts to delineate strength of shared understanding

- Unendorsed option
- Partner decidable option
- Proposal
- Commit

Human-Machine Collaboration to Improve Consistency of Shared Understanding

Features: -- transformed observations that provide an informative basis for inference

• Unendorsed option: speaker “lays” an option with no subsequent actions from others
• Partner decidable option: speaker presents option that requires further balancing of info.
• Proposal: speaker presents an option to be accepted/rejected by the group
• Commit: speaker indicates a full commitment towards an option

Approach

• Low-level classifier: Automatic tagging of dialogue acts (~80% accuracy)
• High-level classifier: HMM inference on group consensus² (~66% accuracy)

Training Set: AMI corpus ~100,000 utterances

Observation: speaker ID with dialogue act tag

Human-Machine Collaboration to Improve Consistency of Shared Understanding

Successful translation of Eugenio's qualitative model into a predictive, statistical ML model

| Prediction Performance of $\text{HMM}_{\text{Eugenio}}$ and Baselines |
|---|---|---|---|---|---|
| $|O|$ | Acc. [%] | Rec. [%] | Prec. [%] | F1 [%] | FPR [%] |
| HMM$_{\text{DAs,full}}$ | 11 | 50.7 | 29.3 | 23.1 | 25.8 | 40.4 |
| HMM$_{\text{DAs}}$ | 4 | 51.4 | 36.5 | 31.0 | 33.5 | 41.1 |
| HMM$_{\text{Eugenio}}$ | 4 | **62.1** | **44.7** | **43.8** | **44.2** | **29.5** |

<table>
<thead>
<tr>
<th>Meeting Phase</th>
<th>Discussion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Project kick-off</td>
<td>Getting acquainted with one another and discussing the project goals</td>
</tr>
<tr>
<td>Functional design</td>
<td>Setting user requirements, technical functionality and working design</td>
</tr>
<tr>
<td>Conceptual design</td>
<td>Determining conceptual specifications for components, properties and materials</td>
</tr>
<tr>
<td>Detailed design</td>
<td>Finalizing user interface and evaluating the final product</td>
</tr>
</tbody>
</table>

Human-Machine Collaboration to Improve Consistency of Shared Understanding

- **Findings:** statistically significant improvement (~18%) in objective measures of teams’ consistency of understanding with intelligent review system

<table>
<thead>
<tr>
<th>Treatment level</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Adaptive review</td>
<td>System suggests review of the two topics with the <strong>lowest</strong> predicted c-scores (weak topics)</td>
</tr>
<tr>
<td>2. Maladaptive review</td>
<td>System suggests review of the two topics with the <strong>highest</strong> predicted c-scores (strong topics).</td>
</tr>
</tbody>
</table>

Inferring hidden mental states enables richer, flexible human-machine teaming

- [Hidden State] What is the current state of our commitment to each decision? — Do we have consensus? What have we agreed to?

- [Hidden State] What is our teammate’s context for decision-making?

Machine observables

Well-established cognitive models

Mental State

Meaningful features that relate to mental state
Model structure to process complex information efficiently
What did we agree to?

Scenario:
• 8 rooms
• B, D, G rooms have patients that need to be rescued
• C, F rooms have leaking valves that need to be fixed
• Robots must inspect the rooms before human crews enter.
What did we agree to?

Scenario:
• 8 rooms
• B, D, G rooms have patients that need to be rescued
• C, F rooms have leaking valves that need to be fixed
• Robots must inspect the rooms before human crews enter.

Trillions of possible solutions ....
What did we agree to?

Scenario:
- 8 rooms
- B, D, G rooms have patients that need to be rescued
- C, F rooms have leaking valves that need to be fixed
- Robots must inspect the rooms before human crews enter.

Using logical structure of planning problem, the inference task becomes almost as easy for a machine as for a person!
Generative model with logic-based prior improves efficiency of inference process

Ordered tuple of sets of grounded predicates

Plan step index assigned to each predicate in utterance $t$

$n^{th}$ predicate that appears in the $t^{th}$ utterance

Relative ordering of predicates in $t^{th}$ utterance as they appear in final plan

Step 1. Do A and B
Step 2. Do C, D and E
Step 3. Do F and G

Generative model with logic-based prior improves efficiency of inference process

1. Perform inference through sampling (Gibbs & MH)

\[ p(\text{plan}) \propto \begin{cases} e^{\alpha} & \text{if plan is valid} \\ 1 & \text{if plan is invalid} \end{cases} \]

Ordered tuple of sets of grounded predicates

\[ \text{n}^{th} \text{predicate that appears in the \( t^{th} \) utterance} \]

Plan step index assigned to each predicate in the \( t^{th} \) utterance

Relative ordering of predicates in \( t^{th} \) utterance as they appear in final plan

---

Successful Automatic Extraction of Final Agreed-Upon Plan

Scenario:
- 8 rooms
- B, D, G rooms have patients that need to be rescued
- C, F rooms have leaking valves that need to be fixed
- Robots must inspect the rooms before human crews enter.

<table>
<thead>
<tr>
<th>Task Allocation</th>
<th>% Inferred</th>
<th>% Noise Rej</th>
<th>% Seq</th>
<th>Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDDL</td>
<td>84</td>
<td>100</td>
<td>91</td>
<td>91</td>
</tr>
<tr>
<td>PDDL with missing goals and constants</td>
<td>100</td>
<td>54</td>
<td>75</td>
<td>76</td>
</tr>
<tr>
<td>PDDL with missing a constraint</td>
<td>88</td>
<td>77</td>
<td>84</td>
<td>83</td>
</tr>
<tr>
<td>No PDDL</td>
<td>85</td>
<td>75</td>
<td>87</td>
<td>82</td>
</tr>
</tbody>
</table>

Technique correctly infers 80-90% of plan, on average.

N=48 distinct plans
Successful Automatic Extraction of Final Agreed-Upon Plan

Scenario:
- 8 rooms
- B, D, G rooms have patients that need to be rescued
- C, F rooms have leaking valves that need to be fixed
- Robots must inspect the rooms before human crews enter.

<table>
<thead>
<tr>
<th>Task Allocation</th>
<th>% Inferred</th>
<th>% Noise Rej</th>
<th>% Seq</th>
<th>Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDDL</td>
<td>84</td>
<td>100</td>
<td>91</td>
<td>91</td>
</tr>
<tr>
<td>PDDL with missing goals and constants</td>
<td>100</td>
<td>54</td>
<td>75</td>
<td>76</td>
</tr>
<tr>
<td>PDDL with missing a constraint</td>
<td>88</td>
<td>77</td>
<td>84</td>
<td>83</td>
</tr>
<tr>
<td>No PDDL</td>
<td>85</td>
<td>75</td>
<td>87</td>
<td>82</td>
</tr>
</tbody>
</table>

Technique correctly infers 80-90% of plan, on average.

N=48 distinct plans
Successful Automatic Extraction of Final Agreed-Upon Plan

Scenario:
- 8 rooms
- B, D, G rooms have patients that need to be rescued
- C, F rooms have leaking valves that need to be fixed
- Robots must inspect the rooms before human crews enter.

<table>
<thead>
<tr>
<th>Task Allocation</th>
<th>% Inferred</th>
<th>% Noise Rej</th>
<th>% Seq</th>
<th>Avg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDDL</td>
<td>84</td>
<td>100</td>
<td>91</td>
<td>91</td>
</tr>
<tr>
<td>PDDL with missing goals and constants</td>
<td>100</td>
<td>54</td>
<td>75</td>
<td>76</td>
</tr>
<tr>
<td>PDDL with missing a constraint</td>
<td>88</td>
<td>77</td>
<td>84</td>
<td>83</td>
</tr>
<tr>
<td>No PDDL</td>
<td>85</td>
<td>75</td>
<td>87</td>
<td>82</td>
</tr>
</tbody>
</table>

Technique correctly infers 80-90% of plan, on average.

N=48 distinct plans
Pentagon touts "Loyal Wingman" for combat jets

30 MARCH, 2016 | BY: JAMES DREW | WASHINGTON DC

US Air Force plans to insert a “brain” into current-generation fighter jets to create autonomous flying wingmen paired with the Lockheed Martin F-35 were given a bump today, with the Pentagon’s second-in-charge saying he expects to see “unmanned wingmen in the air” before convoys of driverless Humvees.

Deputy defence secretary Robert Work touted the long-considered “loyal wingman” concept at a forum hosted by the Washington Post in Washington DC on 30 March, where he explained that the air force will pair unmanned Lockheed F-16s with F-35s in future battles.

Projects with AFRL, Lockheed, and NavAir

Aim:
Demonstrate human-machine collaborative mission planning, pre-mission brief and after-action review for Multi-Platform Air Operations
Inferring hidden mental states enables richer, flexible human-machine teaming

- [Hidden State] What is the current state of our commitment to each decision?

- [Hidden State] What is our teammate’s context for decision-making? – What will we do next?

Machine observables  ?  Mental State

Well-established cognitive models

Meaningful features that relate to mental state
Model structure to process complex information efficiently
Machines that Learn Complex Strategies for Decision-Making from Apprenticeship

Gombolay et al. IJCAI’16, RSS’16

- How to learn complex strategies just by watching?

**ONR makes a serious game of missile defense, electronic warfare**

*BY KEVIN MCCANEY • FEB 04, 2015*

A Navy ship being under missile fire is no game, but making a game of that scenario can help sailors prepare for it.

- Anti-ship missile defense (with MIT LL)

- Coordination of patient care in a hospital
Machines that Learn Complex Strategies for Decision-Making from Apprenticeship

Gombolay et al. IJCAI’16

• Goal: Emulate problem solving capability of human domain experts.

• Approach: Pairwise rank formulation used to train a machine learning model
  
  • Define a set of scheduling-relevant features for the problem
    • E.g. deadline, duration of task, earliest time task is available, resources required by task
  
  • Each observation of expert commitment is described by the feature vector
  
  • Positive and negative training examples computed through pairwise comparison
    • Differences computed for scheduled versus unscheduled tasks
  
  • Classifiers trained to predict highest priority next action to take, and whether to take action at time $t$

\[
\text{rank} \theta^m_{(\tau_i, \tau_x)} := [\xi_{\tau_i}, \gamma_{\tau_i} - \gamma_{\tau_x}], y^m_{(\tau_i, \tau_x)} = 1, \\
\forall \tau_x \in \tau \setminus \tau_i, \forall O_m \in O | \tau_i \text{ scheduled in } O_m \quad (1)
\]

\[
\text{rank} \theta^m_{(\tau_x, \tau_i)} := [\xi_{\tau_x}, \gamma_{\tau_x} - \gamma_{\tau_i}], y^m_{(\tau_x, \tau_i)} = 0, \\
\forall \tau_x \in \tau \setminus \tau_i, \forall O_m \in O | \tau_i \text{ scheduled in } O_m \quad (2)
\]

\[
\widehat{\tau_i} = \arg \max_{\tau_i \in \tau} \sum_{\tau_x \in \tau} f_{\text{priority}} (\tau_i, \tau_x) \quad (3)
\]

\[
\text{act } \phi^m_{\tau_i} := [\xi_{\tau_i}, \gamma_{\tau_i}], \quad (4)
\]

\[
y^m_{\tau_i} = \begin{cases} 
1 : \tau_i \text{ scheduled in } O_m \land \\
\tau_i \text{ scheduled in } O_{m+1} \land \\
0 : \tau_0 \text{ scheduled in } O_m
\end{cases}
\]
Machines that Learn from Watching People Solve Resource Allocation & Scheduling Problems

- Successful application of technique to anti-ship missile defense (with MIT LL)

ONR makes a serious game of missile defense, electronic warfare

BY KEVIN MCCANEY  •  FEB 04, 2015

A Navy ship being under missile fire is no game, but making a game of that scenario can help sailors prepare for it.

- Model trained on 16 demonstrations in which a player mitigated all enemy missiles

- Average human player’s score: 74, 728 ± 26, 824

- Learned model’s average score: 87, 540 ± 16, 842

- Learned scheduling policy performed better than the human demonstrators on more scenarios than vice versa (12 vs. 4 scenarios, p < 0.011)
Machines that Learn Complex Strategies for Decision-Making from Apprenticeship

Gombolay et al. IJCAI’16

- Successful application of technique to anti-ship missile defense (with MIT LL)

- Strategies learned from humans for small problems are used by the machine to quickly solve problems that are too large for the human or machine alone.
Next Steps - From Drones to Teammates

Gombolay et al. RSS’16

- Coordination of patient care in a hospital
Next Steps - From Drones to Teammates

Gombolay et al. RSS’16

- Coordination of patient care in a hospital
From Planning to Flexible Execution

Team Plan Formation

Pre-planning
Do we have consensus?
What have we agreed to?
Apprenticeship
What to do this situation?

Flexible Plan for Execution
From Planning to Flexible Execution

Team Plan Formation

Pre-planning
Do we have consensus?
What have we agreed to?
Apprenticeship
What to do this situation?

Flexible Plan for Execution

Methods for flexible planning and scheduling:

- Multi-Robot Task Allocation & Scheduling at Scale through Schedulability Analysis [RSS’13, JAIS’14]

- Computational techniques for “fair” allocation of resources under uncertainty [NIPS’14, AAAI’15]

- Fast computation of flexible schedules with preferences that accommodate disturbance [RSS’12]

- Multi-level optimization of coordination strategy, allocation and schedule [IJCAI’16]
From Planning to Flexible Execution

Team Plan Formation

- Pre-planning
- Do we have consensus?
- What have we agreed to?
- Apprenticeship
- What to do this situation?

Flexible Plan for Execution

Why is Collaborative Robotics Important?

100% Automation

100% Manual work
From Planning to Flexible Execution

Team Plan Formation

Pre-planning
Do we have consensus?
What have we agreed to?
Apprenticeship
What to do this situation?

Flexible Plan for Execution

Why is Collaborative Robotics Important?

Robots and robotics devices – Collaborative robots

Reduction of NET-B

<table>
<thead>
<tr>
<th>Process No.</th>
<th>Process Name</th>
<th>Process Time</th>
<th>% Time</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>WALK FROM TABLE TO PARTS 1-2 STEPS</td>
<td>60400</td>
<td>14.11%</td>
<td>Net B</td>
</tr>
<tr>
<td>2</td>
<td>GET METER</td>
<td>78100</td>
<td>18.81%</td>
<td>Net A</td>
</tr>
<tr>
<td>3</td>
<td>GET AND ALIGN COUPLER</td>
<td>78100</td>
<td>18.81%</td>
<td>Net A</td>
</tr>
<tr>
<td>4</td>
<td>SET COUPLER</td>
<td>78100</td>
<td>14.11%</td>
<td>Net A</td>
</tr>
<tr>
<td>5</td>
<td>PULL CHECK COUPLER</td>
<td>78100</td>
<td>4.70%</td>
<td>Net B</td>
</tr>
<tr>
<td>6</td>
<td>PLACE METER TO IN PANEL</td>
<td>78100</td>
<td>18.81%</td>
<td>Net A</td>
</tr>
<tr>
<td>7</td>
<td>PACKAGING (A1 30 PER)</td>
<td>78100</td>
<td>10.66%</td>
<td>Net B</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>78100</td>
<td>100.00%</td>
<td></td>
</tr>
</tbody>
</table>

Net B reduction with collaborative robot (For only meter install part): 24.76%
Robots that Plan to Work Flexibly with People

- Real-time processor techniques enable efficient pruning of search space for multi-robot task allocation & sequencing

Computation Time & Schedule Quality for 10-robot Task Allocation & Scheduling

Our Approach: Tercio RSS ‘13

Benchmarks: TeSSi AAAI’15
MILP (Gurobi)
Robots that Plan to Work Flexibly with People

- Efficient computation through Real-time Processor Schedulability Analysis

Our scheduling problem:

Prior approaches provide schedulability tests for restricted problem structure:

Out test relies on worst case analysis of task orderings and resulting idle times

First closed-form polynomial time schedulability test for task sets with upper- and lowerbound temporal constraints

% of Self-Suspension Time Treated as Task Cost or Incurred as Idle Time

Number of Tasks

Number of Subtasks
Robots that Plan to Work Flexibly with People

• Real-time processor techniques enable efficient pruning of search space for multi-robot task allocation & sequencing

Computation Time & Schedule Quality for 10-robot Task Allocation & Scheduling

Our Approach: Tercio RSS ‘13

Benchmarks: TeSSi AAAI’15
MILP (Gurobi)
Prediction enables close-proximity collaborative robotics

Improved team fluency metrics

Leveraging the Biomechanical Model for Fast Target Prediction of Human Motion

Perez D’Arpino et al. ICRA’15, Lasota et al. ICRA’17, Hayes et al. ICRA’17

Building a library of motions (offline, using human motion data)

<table>
<thead>
<tr>
<th>Motion Class</th>
<th>Percentage of Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motion Class 1</td>
<td>73.26%</td>
</tr>
<tr>
<td>Motion Class 2</td>
<td>89.55%</td>
</tr>
<tr>
<td>Motion Class 3</td>
<td>57.08%</td>
</tr>
<tr>
<td>Motion Class 4</td>
<td>85.83%</td>
</tr>
</tbody>
</table>

Average prediction accuracy after observing 20% and 43% of the trajectory

- 20%: 73.26%, 89.55%
- 43%: 57.08%, 85.83%

7 demonstrations, 12 motion classes


* Mainprice, Jim and Berenson, Dmitry: Human-robot collaborative manipulation planning using early prediction of human motion. IROS, 2013
Data from 6 participants, 25 demonstrations collected per participant.
  • Data set aggregates demonstrations from all participants.
  • Random subsampling validation within that data set.

Vaibhav V. Unhelkar**, Claudia Pérez-D’Arpino**, Leia Stirling, Julie A. Shah:
Human-Robot Co-Navigation Using Anticipatory Indicators of Human Walking Motion. ICRA 2015.
** These authors contributed equally to this work.
Contributions

• Approach: translate well-established cognitive models into new computational models that allow machines to
  • infer our mental state
  • process complex information efficiently

Well-established cognitive models

• Experiments validate that these models yield richer, flexible human-machine interactions
  • making higher quality shared plans [IEEE THMS’16, RSS’16 JAIR’15]
  • learning complex shared plans from observation [IJCAI’16]

• Dynamic plan execution supports flexible, real-time teaming
  • multi-robot task allocation and scheduling at scale [RSS’12, RSS’13, NIPS’14, AAAI’15 IJCAI’16]
  • human-aware planning using human motion prediction [ICRA’15a, ICRA’15b, Human Factors ‘15]