CSE 591: Human-aware Robotics

Instructor: Dr. Yu (“Tony”) Zhang

Location & Times: CAVC 359, Tue/Thu, 9:00--10:15 AM
Office Hours: BYENG 558, Tue/Thu, 10:30--11:30AM

Nov 10, 2016

Slides adapted from Subbarao Kambhampati, Heni Ben Amor

This set of slides borrows from various online sources; it is used for educational purposes only.
Challenges in human-aware robotics

- **Perception of humans**
  Human recognition, human tracking, and activity recognition

- **Modeling of humans**
  Goal and intent recognition, human decision and behavioral models, expectation, model learning

- **Human-aware decision making**
  Human-aware planning, reinforcement learning and inverse reinforcement learning

- **Human-robot interface**
  Command recognition, gesture recognition

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"Sit, boy, sit! Sit, I say, Si... Oh, forget it."
## Dimensions of HIL Planning

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Decision theoretic Assistance, Resource conflicts and plan for serendipity, Grandpa hates robots
Model Updates (via natural language)

“To go into a room when you are at a closed door, push it one meter.”

- Precondition: “you are at a closed door”
- Action definition: “push it one meter”
- Effect: “go into a room”

NLP Module

- Reference resolution
- Parsing
- Background knowledge
- Action submission (to planner)

[In collaboration with hrilab, Tufts University]

[Cantrell, Talamadupula et al., HRI 2012]
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Decision theoretic Assistance, Resource conflicts and plan for serendipity Grandpa hates robots + ...
Challenges in Human-Aware Planning & Decision Making

• Interpret what humans are doing
  – Plan/goal/intent/preference/capability recognition (Expectation)

• Plan with incomplete domain models
  – Robust planning with “lite” models
  – (Learn to improve domain models)

• Continual planning/Replanning
  – Commitment sensitive to ensure coherent interaction

• Explanations/Excuses
  – Excuse generation can be modeled as the (conjugate of) planning problem

• Asking for help/elaboration
  – Reason about the information value
Explicability among Humans

• We, as humans, while interacting make an effort (behave explicably) to be understood.

• Explicability is crucial for good team performance.
Explicability

Explicability is not only important for human-human teams but also for human-robot teams.

Goal: Clear a cluttered table

- Move to the table
- Push the items off the table
- Pick and place
- Table is clear

- Move to the table
- Keep books on shelf
- Remove the coffee mug
- Place pen in pen holder
- Table is clear

Human’s expectation of agent behavior

Hidden in human’s mind
Explicability

Explicability is not only important for human-human teams but also for human-robot teams.

Goal: Clear a cluttered table

- Move to the table
- Push the items off the table
- Pick and place

Table is clear

- Keep books on shelf
- Remove the coffee mug
- Place pen in pen holder

- Expectations are not met
- Inexplicable

Crucial for an agent to understand other agent’s interpretation of itself.

- Confusion and surprise
- Cognitive load
- Safety concerns
Plan Explicability for Autonomous Robots

Autonomously construct task plans

Goal: Clear a cluttered table

Move to the table

Move to the table

Keep books on shelf

Remove the coffee mug

Place pen in pen holder

Table is clear

Push the items off the table

Candidate plan #1 (Cost optimal plan)

Candidate plan #2

...
Plan Explicability

How do we compute the plan explicability measure?

- Human’s expectation of an agent is associated with another model of the agent in human’s mind.
- Plan explicability can be interpreted as a “distance” between the plans generated by $M_R$ and $M_R^*$. 
Problem Formulation

Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between the robot plan and human’s expectation of the robot plan:

\[
\arg\min_{\pi_{MR}} \text{cost}(\pi_{MR}) + \alpha \cdot \text{dist}(\pi_{MR}, \pi_{MR}^*)
\]
Plan = \{ a_1, a_2, a_3 ... a_n \}

The easier it is for humans to associate tasks/sub-goals to a plan, the more explicable the plan is.

How do we obtain $M_{R^*}$?

- Human’s understanding of the other agents’ behavior is related to how we associate it with tasks.

The easier it is for humans to associate tasks/sub-goals to a plan, the more explicable the plan is.

Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between the robot plan and human’s expectation of the robot plan:

$$\arg\min_{\pi_{MR}} \text{cost}(\pi_{MR}) + \alpha \cdot \text{dist}(\pi_{MR}, \pi_{M^*_R})$$
Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between the robot plan and human’s expectation of the robot plan:

$$\arg\min_{\pi_{MR}} \text{cost}(\pi_{MR}) + \alpha \cdot \text{dist}(\pi_{MR}, \pi_{M^*_R})$$

$$\text{dist}(\pi_{MR}, \pi_{M^*_R}) = F \circ \mathcal{L}^*(\pi_{MR})$$

Function that takes plan labels as input

Human’s labeling scheme for robot plans
Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between the robot plan and human’s expectation of the robot plan:

$$\arg\min_{\pi_{MR}} \text{cost}(\pi_{MR}) + \alpha \cdot \text{dist}(\pi_{MR}, \pi_{M^*_{R}})$$

$$\text{dist}(\pi_{MR}, \pi_{M^*_{R}}) = F \circ \mathcal{L}^*(\pi_{MR})$$

$$\arg\min_{\pi_{MR}} \text{cost}(\pi_{MR}) + \alpha \cdot F \circ \mathcal{L}^*_{CRF}(\pi_{MR} | \{S_i | S_i = \mathcal{L}^*(\pi_{i_{MR}})\})$$

Learned labeling scheme function using linear chain Conditional Random Fields
Explicability labeling for obtaining training samples

Task labels for actions. For example:
- Collect
- Store
- Observe

\[
\arg\min_{\pi_{MR}} \text{cost}(\pi_{MR}) + \alpha \cdot F \circ \mathcal{L}_{CRF}^*(\pi_{MR} | \{S_i | S_i = \mathcal{L}^*(\pi_{MR}^i)\})
\]
Learning using CRF

Model:
- Conditional Random Fields (CRF)

Task labels for actions. For example:
- Collect
- Store
- Observe

Features:
- Plan features: state, e.g., at rover 5; action name, e.g., rover

\[
p(x, y) = \frac{1}{Z} \prod_A \Phi(x_A, y_A)
\]

\[
\arg\min_{\pi_{MR}} \text{cost}(\pi_{MR}) + \alpha \cdot F \circ \mathcal{L}^*_{CRF}(\pi_{MR} | \{S_i | S_i = \mathcal{L}^* (\pi_{MR}^i)\})
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Plan Explicability for Autonomous Robots

Given N candidate plans

Autonomously construct task plans

Candidate plan #1
(Cost optimal plan)

...Candidate plan #k

Filtered by plan explicability measure

Explicable Plan
Implemented Scenario

Goal: build a tower of height 3

Heavy block is on the left

www.youtube.com/watch?v=AAAwSVbAV7s
Interactive teaming

\[
\arg\min_{\pi_{MR}} \text{cost}(\pi_{MR}) + \alpha \cdot \text{dist}(\pi_{MR}, \pi_{M^*})
\]

\[
\arg\min_{\pi_{CM}} \text{cost}(\pi_{CM}, \overline{M_H}) + \alpha \cdot \text{dist}(\pi_{CM}, \overline{M_H}, \pi_{CM}, M_H)
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\]
Interactive teaming

(Team) working on a tower
Robot in action
Related work

• There exists work on generating legible robot motions
• Two different task plans may map to the exact same motions
  ➢ Plan explicability is focusing on task planning

• Model learning via learning from demonstration, inverse reinforcement learning, cross-training, and tutoring systems
• Previous approaches are about how one agent teaches the other agent in terms of its plan preference
• Note that a preferred plan may not always be an expected plan; similarly, an expected plan may not always be a preferred plan

  ➢ We are addressing the question of what humans would expect the robot to do rather than what humans themselves would do
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A Generalized Model of Replanning

- **PLANNER**
  - Input: \(<l, G>\)
  - Output: PLAN

- **PLAN**
  - Input: From PLANNER
  - Output: EXECUTION

- **EXECUTION**
  - Input: PLAN
  - Output: Publicize to Other Agents

- **CONSTRAINT PROCESSING**
  - Input: PLAN
  - Output: Constraint Constraints
  - Feedback to PLAN

- **MONITORING**
  - Input: From EXECUTION
  - Output: \(<l', G', \psi>\)

- **WORLD**
  - Input: \(<l, G>\)
  - Output: EVENT

- **Present for Assessment**
  - Input: From EXECUTION
  - Output: To PLANNER

- **Similarity Constraints**
  - Feedback from EXECUTION to CONSTRAINT PROCESSING

- **Commitment Constraints**
  - Feedback from CONSTRAINT PROCESSING to EXECUTION
Failures in Planner-Based Systems

When acting in a uncertain, dynamic environment, things can go wrong:

- Execution failures
  - Error diagnosis
  - Continual Planning
- Planning failures
  - Domain is incorrectly modelled
  - Incomplete world knowledge
  - Missing resources
  - Maybe the task is just unsolvable

Coming up With Good Excuses
Projecting robot intents

- Tracking
- Planning
  - Projection Recommender
  - Capability Model
- Execution
  - Plan
    - Move
    - Turn
    - Signal
Hand me the white leg that is on the table.

\( \gamma \) are groundings, or objects, places, paths, and events in the external world. Each \( \gamma \) corresponds to a constituent phrase in the language.
Other Challenges in Human-aware Robotics
Trust in human-robot teaming

Trust building

When to trust

Mutual trust

Emergencies
In emergencies, don’t trust a robot too much
Published 1 March 2016

In emergencies, people may trust robots too much for their own safety, a new study suggests. In a mock building fire, test subjects followed instructions from an “Emergency Guide Robot” even after the machine had proven itself unreliable — and after some participants were told that robot had broken down.

Simulation of rescue robot in operation // Source: gatech.edu
Cyber-physical systems
Safety in Human-robot Teaming

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings, except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.
Artificial Intelligence, Employment, and Income

Nils J. Nilsson

Abstract

Artificial intelligence (AI) will have profound societal effects. It promises benefits (and may also pose risks) in education, defense, business, etc. In this article we explore how AI is likely to affect employment and the distribution of income. We argue that AI will indeed reduce drastically the need of human workers for activities other than our present jobs, we ought thus to greet the welfare consequences of AI enthusiastically. The paper discusses two reasons why this optimistic appraisal may be false.
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"Sit, boy, sit! Sit, I say, Si... Oh, forget it."

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"R.O.B.O.T. Comics"

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"Willow Garage"