LAAS-CNRS

Doctoral Thesis

Decision Making in Human-Robot Interction

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Abstract

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Doctor of Philosophy in Robotics

Decision Making in Human-Robot Interction

by Michelangelo FIORE

My abstract

Version française

Mon Abstract

Acknowledgements

TODO...

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Chapter 1

Introduction

In the current days robots are starting to get introduced in our daily lives more and more, and we can expect them, in the next years, to complete the transition from mechanic tools, used mostly in industries, to true partners and companions. There is an increasing interest in studying how robots should behave in human habited environments, with some researchs deploying robots in crowded, and dynamic, environments like airports and museums.

Human-Robot cooperation poses a multitude of problems. Imagine a mobile robot working in a warehouse, moving in the area to carry crates, sorting them in different locations. Already, we are presented with a quite complex problem. The need to be able to have a good representation of the world (i.e. position of the crates, obstacles, layout of the warehouse), to create plans to reach its goals (which crates to move, where to bring them, which path to follow), and to have sufficient motion and manipulation skills to achieve them. If humans are present in the environment, they should be represented and considered by the robot in its plans and actions. Representing humans as simple moving obstacles might not be enough if we consider issues of trust, legibility, and acceptability. The robot should respect a number of social rules in the presence of humans, like maintaining a socially acceptable distance, whenever possible, from them, or not approaching from outside their field of view.

The problem becomes even more complex when robots and humans need to cooperate to solve a goal, for example by cooperating to sort the crates, or even by carrying heavy objects together. To have some insight on how to approach this problem we can observe how humans cooperate with themselves. Psychological and philosofical research characterizes the execution of cooperative actions as 'joint actions'. Sebanz et al. have proposed that the execution of a joint action depends on three different abilities: sharing representations, predicting actions, integrating predicted effects of own and other's actions. These abilities can be achieved by the integration of different mechanisms:

- Joint Attention: the ability to direct a partner's attention, in order to create a shared representation of objects and events. Humans possess a large number of social cues, like gaze direction or pointing gestures, to indicate what is currently under observation. This mechanism helps filling important gaps in the knowledge of a partner, and points to the importance of understanding what other partners know and perceive.

- Action Observation: observing other partner's actions is crucial in understanding what are their goals. Studies have shown that observing a person performing an action produces a motor resonance, which incresease with the observer's level of expertise in the action, and allows to predict the effect of the agent's action on the world, and even his next actions.

- Task Sharing: humans are able to predict, in some circumstances, what others will do even without direct observation. It's the case of well trained sports team, which are able to act like a single entity, coordinating seamlessly. This ability suggests that humans need to possess a shared representation of tasks, which include other's expected actions.

- Action Coordination: predicting other's action is not enough. Humans also need to choose a complementary action, and adjust it in time and space to partners.

It seems that robots need to have an equivalent of these mechanism, in order to cooperate in a natural and acceptable way with humans. We could ask ourselves if this is enough to include robots in our daily lives. Unfortunately, we just scratched the surface of the problem. While these areas are already very comples, and not completely understood, humans possess other complex skills, that should be translated to robots. For example, when a robot's behavior shows a degree of intelligence, humans usually try to have a conversation with it, which can lead to frustation, or often disbelief in the actual capacities of the robot. Issues such as dialogue, representation and refinement of knowledge are very complex and won't be a direct focus of this work.

The goal of this thesis is, instead, to provide a framework to allow a robot to work in social environments and execute joint actions with humans in a natural way. We built our system using psychology as an inspiration, without trying to replicate accurately human mechanism, an area of work studied in cognitive systems.

1.1 Contributions

The main contributions of this work are the following:

- Building a supervision system for human robot interaction, integrating novel algorithms developed in this work with existing, components.

- Developing a novel algorithm to infer human goals and intentions.

- Developing a novel probabilistic planning algorithm for multiple agent

1.2 Terminology

- Agent: a human or a robot.

- Action: a tuple $(name, preconditions, target, postconditions)$. The *name* of an action is a unique string that identifies it. The *preconditions* are a list of properties that must be true in order to realize the action. In our system, an action is executed on a *target*, which can be a physical object, like a cup, but also an area of the environment, like a room. The *postconditions* are the set of properties, and their values, affected by the action's execution.

1.3 System overview

The supervision system was developed with the following goals in mind:

- Flexibility: the system is able to work in different scenarios and environment, with different robots, and have a minimum impact on the code.
- Extendibility: the system can be easily extendable by adding or substituting modules, to introduce different capacities.
- Human-Awareness: the system is built with human-robot cooperation in mind. It supports human belief management, multi-agent planning, human-aware motion and execution, and simple forms of direct interaction.

To achieve this goal we chose to use the well known ROS framework, which allows use different robots without having a large impact on the code.The system has been implemented and tested in simulation, using the GAZEBO simulator, and on two different robots, the PR2 by Willow Garage, and the SPENCER robot, developed in an european project.

The supervision system is composed by the following modules:

- Situation Assessment: this modules produces symbolic information, using geometrical and temporal reasoning, starting from perception data. Using Situation Assessment, the robot is able to understand information such as if an object is reachable, if an human has performed an action, and if a human is heading toward it.
- Symbolic Database: this module collects all the symbolic information produced by the system. The Database is able to represent the knowledge of different agents, as viewed by the robot. Using this feature, the robot can represent, for example, the fact that a human doesn't know the location an object, or thinks that it is in a wrong place.
- Goal Manager: this module chooses a manages the different goals of the robot. The module chooses a goal starting from information produced by Situation Assessment and present in the database. These information can be inferred by the robot's reasoning algorithm (e.g. the robot infers that the human is looking for his glasses, so it creates a goal to fetch them), or directly given by a human (e.g. the human asks the robot to fetch his glasses).
- Plan Manager: This module contacts the Task Planner to produce plans to achieve the current goal, and then manages these plans. The system supports multi-agent plans, and so the Plan Manager will monitor other agents action, to check if they conform to the current plan, and interact with the Execution Manager module to execute the robot's actions. The Plan Manager will handle replans, when an action executed by the robot fails or other agents's behavior differ from the current plan.

- Execution Manager: this module handles the execution of robot's action, including joint actions shared with other agents. The module handles different situation that can arise while executing an action, for example stopping and resuming it or abandoning it.

The system also interfaces itself with other modules, which can be easily changed depending on the current needs:

- Task Planner: this module is an abstraction for different Task Planner that can be used by the system. Different planners can be introduced in the system, by creating a new module that respects the conventions used by the Plan Manager.
- Motion Planners: this modules are used by the Execution Manager to plan the robot movements and actions. The system uses the Geometrical Task Planner (GTP) to plan manipulation actions and the well known Move Base stack for navigation planning.
- Motion Execution: this module executes trajectories planned by the Motion Planners. The system uses the Pr2Motion executor.

1.4 Organization of the Thesis

1.5 Published Works

Chapter 2

Situation Assessment

In this chapter we introduce the Situation Assessment capacities of our system.

2.1 Introduction

For any application that's not repetitive, control based, it's necessary that robots have a representation of their environment. Depending on the application, these information could be simple or more complex. Imagine, for example, a robot that needs to clean the floor of a room. A simple implementation of this idea would rely on a map of the room and laser or bumper sensors to avoid or detect obstacles. Now, imagine a household robot that needs to actively help a family that lives in an apartment, by fetching objects, providing information and help accomplish various tasks. Clearly, in this situation, the robot needs a deeper degree of reasoning on sensor data: laser points and camera images need to be integrated to recognize objects and humans, spatial relationships between objects (e.g. the cup is on the table) and humans (e.g. the human has the cup) need to be properly modeled, actions performed by humans, and their effects on the environment, need to be recognized, and so on.

In this situation, there is a need for a module that performs different kind of reasoning on perceptual data, and produces information that can be used by the rest of the system. Maintaning knowledge and understanding of the current situation, also known as situation awareness, is called situation assessment. Endsley in **?** explains that "situation awareness incorporates an operator's understanding of the situation as a whole, forming the basis for decision making".

2.1.1 Situation Assessment

A variety of robotic systems have made a situation assessment component to fit the need of the robot in a particular task application. In **?**, the situation assessment system is based on Dynamic Markov chains to model the environment states and their evolution. It presents an application for a mobile robot to navigate in a narrow passage. **?** aims to build a "higher order" perception, giving the robot the ability to reason on its own inner world. **?** presents an empirical assessment of situations for a mobile robot in a crowded public environment applied to recognize situations of deliberate obstruction. In our situation assessment software we focus on what is represented (human, objects ...) and we support heterogeneous type of sensors and data to provide a semantic interpretation of the environment with the aim to have a situation assessment capability that can be used in a various set of applications (see **??**).

2.1.2 Theory of Mind

perceptual perspective taking, whereby human can understand that other people have a different perception of the world, and 2) conceptual perspective taking, whereby humans can go further and attribute beliefs and feelings to other people **?**.

Understanding properly others' intention requires to reason about their beliefs and thoughts, and on how they affect actions. This skill is called Theory of Mind **?**. An ability linked to this concept is perspective taking, which is widely studied in developmental literature. Flavell in **?** describes two levels of perspective taking: 1) perceptual perspective taking, whereby humans can understand that other people see the world differently **?**, and 2) conceptual perspective taking, whereby humans can go further and attribute thoughts and feelings to other people **?**. Studies on individuals that don't possess the required mechanisms to perform perspective taking, like young children **?**, have put into light the difficulties these people have to accomplish everyday social relationships and confirmed the importance of this ability.

Previous works in robotics have shown that enhancing the robot's perspective taking abilities improves its reasoning capabilities, leading to more appropriate and efficient task planning and interaction strategies **???**.

Concerning level two, various research on human robot interaction already aim to represent the human belief state. Breazal et al. **?** proposed one of the first human-robot implementation. In our previous work **?**, we made a primitive implementation to solve the Sally and Anne test described by Wimmer in **?**. In this primitive implementation, the reasoning on others belief state was limited to object position. We propose here a more generic approach to represent any kind of belief the human may hold on the environment.

The first point we need to introduce is the concept of intention. There are many different definitions of intention in psychology **?** and philosophy **?** literature. In this paper we define an intention as the wish and will to achieve a goal. The intention emerges from contextual causes (motivations) and is present

An important study linked to conceptual perspective taking is the 'divergent belief task'. Formulated in **?**, this kind of task requires the ability to recognize that others can have beliefs about the world that differ from the observable reality. **?** proposed one of the first human-robot implementations, resulting in more advanced goal recognition skills. This is a primary issue of intention recognition, since, as explained by **?** "as humans, we generally believe that others act in ways that are consistent with their beliefs and goals".

Also, the authors's belief modeling (described fully in **?**) is oriented toward communication problems and not geometrical and spatial perspective taking issues.

2.1.3 Activity Recognition

The recognition of human activities is an important topic in computer science research, which can be studied at different levels. Anticipating human actions and movements allows the robot to adapt its behavior and proactively help humans, as studied in **?**. An interesting idea is using the robot's own internal models in order to recognize actions and predict user intents, as shown by the *HAMMER* system in **?**. Sequences of actions can be linked to plans, a well-known topic called plan recognition. Several approaches have been studied in this domain using, for example, classical planning **?**, probabilistic **?** or logic techniques **?**. An interesting framework for intention recognition is the Bayesian Theory of Mind **?**, used to represent the inference process of an observer looking at another agent's behaviors, with POMDPs and Dynamic Bayesian Networks (DBNs).

Two approaches that can be used for intention estimation are Interactive Partially Observed Markov Decision Processes (I-POMDP) and Inverse Learning. I-POMDP **?** offer a rich framework that extends Partially Observed Markov Decision Processes (POMDP) in a multi-agent setting. Inference in these models can be extremely complex, but there have been attempts at solving this issue, like in **??**.

Inverse Reinforcement Learning **?** formulates the problem of computing an unknown reward function of an agent after observing his behavior. This strategy has been applied, with Bayesian Networks (BN), in **?**, in order to learn the mental model of another agent, and choose appropriate actions for a relationship building task. A linked approach is inverted planning, which has been applied in a bayesian framework in **?** for human action understanding.

Contextual information can be used to further disambiguate complex situations. **?** shows a system using BNs to understand users' intentions with an emphasis on contextual information.

2.2 Definitions

2.3 Situation Assessment

2.3.1 Entity Recognition

2.4 Belief Management

2.5 Action and Intention Inference

2.5.1 Intention Graph

2.5.2 Context to Intentions

2.5.3 Intentions to Actions

2.5.4 Actions to Observations

2.5.5 Inference Process

2.6 Experiments

2.6.1 Case Study

2.6.2 Robot Implementation

2.6.3 Discussion