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Plan-Based Social Interaction with a Robot Bartender

Ronald P. A. Petrick
School of Informatics
University of Edinburgh
Edinburgh EH8 9AB, Scotland, UK
rpetrick@inf.ed.ac.uk

Mary Ellen Foster
School of Mathematical and Computer Sciences
Heriot-Watt University
Edinburgh EH14 4AS, Scotland, UK
M.E.Foster@hw.ac.uk

Abstract
A robot coexisting with humans must not only be able to perform physical tasks, but must also be able to interact with humans in a socially appropriate manner. We describe an application of planning to task-based social interaction using a robot that must interact with multiple human agents in a simple bartending domain. The resulting system infers social states from low-level sensors, using vision and speech as input modalities, and uses the knowledge-level PKS planner to construct plans with task, dialogue, and social actions.

Introduction and Motivation
As robots become integrated into daily life, they must increasingly deal with situations in which socially appropriate interaction is vital. In such settings, it is not enough for a robot simply to achieve its task-based goals; instead, it must also be able to satisfy the social goals and obligations that arise through interactions with people in real-world settings. As a result, a robot not only requires the necessary physical skills to perform objective tasks in the world, but also the appropriate social skills to understand and respond to the intentions, desires, and affective states of its interaction partners.

To address this challenge, we are investigating task-based social interaction in a bartending domain, by developing a robot bartender (Figure 1) that is capable of dealing with multiple human customers in a drink-ordering scenario.

Key to our approach is the use of high-level planning techniques, which are responsible for action selection and reasoning in the robot system. Specifically, we use the knowledge-level planner PKS (Petrick and Bacchus 2002; 2004), a choice that is motivated by PKS’s ability to work with incomplete information and sensing actions: not only must the robot perform physical tasks (e.g., handing a customer a drink), it will often have to gather information it does not possess from its environment (e.g., asking a customer for a drink order). Moreover, since interactions will involve human customers, speech will be the main input modality and many of the planner’s actions will correspond to speech acts, providing a link to natural language processing—a research field with a long tradition of using planning, but where general-purpose planning techniques are not the focus of mainstream study.

Robot System Architecture and Components
The target application for this work is a bartending scenario, using the robot platforms shown in Figure 1. The robot hardware itself (Figure 1) consists of two 6-degrees-of-freedom industrial manipulator arms with grippers, mounted to resemble human arms. Sitting on the main robot torso is an animatronic talking head capable of producing facial expressions, rigid head motion, and lip-synchronised synthesised speech. For testing and demonstration purposes, the simulated robot shown in Figure 1 is also available.

A sample interaction in a simple bartending scenario is shown in Figure 2. In this example, two customers enter the bar and attempt to order a drink from the bartender. When
A customer approaches the bar and looks at the bartender

CUSTOMER 1: A pint of cider, please.

Another customer approaches the bar and looks at the bartender

CUSTOMER 2: I’d like a pint of beer.

Figure 2: An example interaction in the bartending scenario.

low-level sensor data and the high-level structures used by components like the planner. Since states are induced from the mapping of sensor observations to fluent values, the challenge of building an effective state manager rests on defining appropriate mapping functions.

In the bartender robot, we treat each low-level input component as a set of sensors. The linguistic interpreter corresponds to three sensors: two that observe the parsed content of a user’s utterance and its associated confidence score, and another that returns the estimated angle of the sound source. The vision system also senses a large number of properties about the agents and objects in the world, each of which corresponds to a set of individual sensors. Certain low-level output components are also treated as sensors. For example, the robot arms provide information about the start and end of manipulation actions, while the speech synthesiser reports the start and end of all system utterances. Modelling output components as sensors allows information from these sources to be included in the derived state, ensuring the current state of interaction is accurately reflected (e.g., the state of turn-taking or the completion of physical actions).

In the current robot bartender system, the state includes information about all agents in the scene: their locations, torso orientations, attentional states, and drink requests if they have made one. The mapping from sensors to states is rule-based. One set of rules infers user social states (e.g., seeking attention) from the low-level sensor data, using guidelines derived from a study of natural bartender interactions (Huth 2011). The state manager also incorporates rules that convert the logical forms produced by the parser into communicative acts (e.g., drink orders), and that use the source angle from the speech recogniser together with the vision properties to determine which customer is likely to be speaking. A final set of rules determines when new state reports are published, which controls turn-taking.

To deal with the more complex states required in future versions of the bartender system, we are currently exploring the use of supervised learning classifiers trained on multimodal corpora. In an initial study, the trained classifiers significantly outperformed the hand-coded rules both in cross-validation and when tested with real users (Foster 2013).

Planning and Execution Monitoring: The high-level planner is responsible for taking state reports from the state manager and choosing actions to be executed on the robot. Plans are generated using PKS (Planning with Knowledge and Sensing) (Petrick and Bacchus 2002; 2004), a conditional planner that works with incomplete information and
sensing actions. PKS operates at the knowledge level and reasons about how its knowledge state, rather than the world state, changes due to action. To do this, PKS works with a restricted first-order representation with limited inference. While features such as functions and run-time variables are supported, these restrictions mean that some types of knowledge (e.g., general disjunctive information) cannot be modelled. To ensure efficient inference, PKS restricts the type of knowledge it can represent to a set of four databases:

- $K_f$: This database is like a STRIPS database except that both positive and negative facts are permitted and the closed world assumption is not applied. $K_f$ can include any ground literal or function (in)equality mapping $\ell$, where $\ell \in K_f$ means "the planner knows $\ell$.”

- $K_w$: This database models the plan-time effects of “binary” sensing actions. $\phi \in K_w$ means that at plan time the planner either "knows $\phi$ or knows $\neg \phi$," and that at run time this disjunction will be resolved. PKS uses such information to build conditional branches into a plan.

- $K_v$: This database stores functions whose values will become known at run time. In particular, $K_v$ can model the plan-time effects of sensing actions that return terms. $K_v$ can contain any unnested function, where $f \in K_v$ means that at plan time the planner "knows the value of $f$.”

- $K_e$: This database models the planner’s “exclusive-or” knowledge. Entries in $K_e$ have the form $(\ell_1|\ell_2|...|\ell_n)$, where each $\ell_i$ is a ground literal. Such formulae represent a type of disjunctive knowledge common in planning domains, namely that "exactly one of the $\ell_i$ is true.”

A PKS action is modelled by a set of preconditions that query PKS’s knowledge state, and a set of effects that update the state. Preconditions are a list of simple questions about PKS’s knowledge state (e.g., a query $K(\phi)$ asks if $\phi$ is known). Effects are described by a set of STRIPS-style “add” and “delete” operations that modify the contents of individual databases. E.g., $\text{add}(K_f, \phi)$ adds $\phi$ to the $K_f$ database, while $\text{del}(K_w, \phi)$ removes $\phi$ from $K_w$. PKS constructs plans by reasoning about actions in a simple forward-chaining manner, and can build plans with branches by considering the possible outcomes of its $K_w$ and $K_e$ knowledge. Goals are specified in a form similar to action preconditions.

PKS is also aided by an execution monitor which controls replanning. The monitor takes as input a PKS plan, and a description of the sensed state provided by the state manager. The monitor must assess how close an expected, planned state is to a sensed state in order to determine whether the current plan should continue to be executed. To do this, it tries to ensure that a state still permits the next action (or set of actions) in the plan to be executed, by testing an action’s preconditions against the current set of (sensed) state properties. In the case of a mismatch, the planner is directed to build a new plan, using the sensed state as its initial state.

Output Generation: Output in the system is based on dividing actions selected by the planner into speech, head motions, and arm manipulation behaviours that can be executed by the robot. To do so, we use a structure containing specifications for each of the output modalities (Isard and Mathe-son 2012), based on a rule-based approach which splits each planned action into its component subparts. The resulting structure is then passed to the multimodal output generator, which sends specific commands to each output channel.

OpenCCG is used to generate speech output for the robot, using the same grammar that is used to parse the input. The output description is specified in terms of high-level communicative acts, which are translated into logical forms and sent to the OpenCCG realiser. The realiser then outputs text strings that are turned into speech by the robot’s animatronic head. In addition to speech, the robot also expresses itself through facial expressions, gaze, and arm manipulation actions. The animatronic head can produce a number of expressions and can gaze at customers or objects, while the robot arm can perform tasks like grasping to hand over a drink to a customer; motion planning and robot control make use of the Robotics Library (Rickert 2011).

System Integration: Like most interactive multimodal systems, the robot bartender is made up of a number of distributed, heterogeneous software components, drawing on diverse research paradigms, each with individual hardware and software requirements. These components must all communicate with one another to support interactions in the bartender scenario. The planner must also be situated in this system and use the same interfaces as other components.

For inter-module communication in the robot bartender, we use the Ice object middleware (Henning 2004), which provides platform- and language-independent communication among the modules and supports direct module-to-module communication as well as publish-subscribe messaging. On the planning side, adapting the off-the-shelf PKS planner for use with Ice is achieved by creating a communication-level API to common planning features, and re-engineering the backend planner into a suitable library that supported this interface. Common operations like planner configuration, domain definition, and plan construction were abstracted into a class definition that allowed a PKS planner instance to be created as a C++ object. The interface to this library was built into a simple server which provided a transparent network interface to its functions over Ice.

Planning Interactions for Social Behaviour The robot’s available high-level actions are modelled as part of a PKS planning domain, rather than using specialised tools as is common in many dialogue systems. For instance,
the basic bartender domain consists of the following actions, available to the robot for interacting with human customers:

- `greet(a)` greet an agent ?a,
- `ask-drink(a)` ask agent ?a for a drink order,
- `ack-order(a)` acknowledge agent ?a’s drink order,
- `serve(a, ?d)` serve drink ?d to agent ?a,
- `bye(a)` end an interaction with agent ?a,
- `not-understand(a)` inform agent ?a was not understood,
- `wait(a)` tell agent ?a to wait, and
- `ack-wait(a)` thank agent ?a for waiting.

Actions model high-level robot behaviours that include a mix of physical, sensory, and speech acts. Examples of two PKS actions in the bartender domain are shown in Figure 4.

Information about human agents is not hard-coded in the domain but is detected by the vision system and passed to the planner by the state manager through its state updates. Similarly, changes to the agent list are also sent to the planner in state reports, causing it to update its domain model. The goal is simply to serve each agent seeking attention. This goal is viewed as a rolling target which is reassessed each time a state report is received by the planner. For instance, if two agents (a1 and a2) are seeking attention, PKS can build the following plan (similar to the interaction in Figure 2):

```
greet(a2),
greet(a1),
ask-drink(a1),
ack-order(a1),
serve(a1, request(a1)),
bye(a1),
ack-wait(a2),
ask-drink(a2),
ack-order(a2),
serve(a2, request(a2)),
bye(a2).
```

Here, a1’s drink order is taken and processed, followed by a2’s order. The `ask-drink` action is a sensing action that returns information about the term `request` (an agent’s drink order), which is then used as a run-time variable in the `serve` action. The `wait` and `ack-wait` actions are used to defer a transaction with a2 until a1’s transaction has finished.

Once a plan is built, it is executed by converting each action into its head, speech, and arm behaviours, based on a simple set of rules. Execution is monitored for plan correctness by comparing states from the state manager against states predicted by the planner. In the case of divergence, the planner is directed to construct a new plan using the sensed state as its new initial state. For example, if a1’s response to `ask-drink(a1)` was not understood, the execution monitor will direct PKS to build a new plan. One result is a modified plan that first informs a1 they were not understood before repeating the `ask-drink` action and continuing the old plan.

Another consequence of execution monitoring is that certain types of overanswering can be detected and handled through replanning. For instance, a `greet(a1)` action by the robot might cause the customer to respond with an utterance that includes a drink order. In this case, the monitor would detect that the preconditions of `ask-drink(a1)` aren’t met and direct PKS to replan. A new plan could then omit `ask-drink` and proceed to acknowledge and serve the requested drink.

The complete bartender system uses the physical or simulated robot to process interactions similar to those shown above. Users interact with the system using speech, while the main system interface (Figure 5) displays the reasoning and execution status of the core components, including planning and state management.

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**References**


