Robot Learners: Interactive Instance-based Learning and Its Application to Therapeutic Tasks

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Abstract

Programming a robot to perform tasks requires training that is beyond the skill level of most individuals. To address this issue, we focus on developing a method that identifies keywords used to convey task knowledge among people and a framework that uses these keywords as conditions for knowledge acquisition by the robot learner. The methodology includes generalizing task modeling and providing a robot learner the ability to learn and improve its skills through accumulated experience gained from interaction with humans. More specifically, the aim of this research addresses the issues of knowledge encoding, acquisition, and retrieval through interactive instance-based learning (IIBL). In interaction studies, the benefit of using such a robot learner is in promoting social behaviors that results from the participant taking on an active role as teacher. Our recent experiment with 33 participants, including 19 typically developing children, and a pilot study with two children with autism spectrum disorder showed that IIBL provides a framework for designing an effective robot learner, and that the robot learner successfully increases the amount of social interactions initiated by the participants.

Introduction

For robots to become true "personal companions", non-expert users should be able to customize their robot's skills or teach new ones intuitively. In this work, our motivation is to minimize the difficulties clinicians face when using robots as therapy mediators. Until now, most robot therapeutic devices were teleoperated, exhibited simple reactive behaviors, or were limited to conducting a single task. With our proposed robot learner, non-expert individuals may train their robots to conduct tasks such as addressing each patient's individual needs. A secondary benefit is the ability to foster social interaction through child-robot play interaction that is directed by the child, thus moving towards interventions that can be translated outside of the clinical setting (Gartner et al. 1971). To enable this setting, we utilize an interactive instance-based learning (IIBL) method. In instance-based learning, "snapshots" or instances of experience representing the task-feature space and resulting actions are stored as state-action pairs for later retrieval (Aha et al. 1991). A knowledge base is constructed from these pairs by addressing the methods of *encoding* a given instance by reducing the task-feature space based on input from the user, *acquiring* instances that auto-populate the data base through encoding user demonstrations, and *retrieving* instances by determining the optimal similarity measure between itself and the nearest instances of the query.

The overarching research objectives are: 1) To ensure the IIBL framework effectively models tasks by utilizing demonstrations from the user even when an explicit model of the problem domain is difficult to elicit and is not amenable to complete mathematical modeling, 2) To validate that the robot's learning behavior and performance positively impacts the length of interaction and the social behavior of the user. In order to support these objectives, we measure how well and efficiently the robot learns a task from human demonstration, measure the occurrences and the length of initiated interactions, analyze the emerging social behavior from the user depending on the robot's learning strategies, and conduct a post-experiment survey to evaluate user experience (Park 2014).

Interactive Instance-based Learning

Instance-based learning methods store training instances in a raw form and postpone generalization until the instance-query time. When a new instance is introduced, its classification relies on the stored data and the similarity computed between the new and previous instances (Kolodner 1991). In this work, we combine interactive methods to address the hindrances of automating the processes of instance encoding, acquisition, and retrieval in instance-based learning methods. Some previous efforts have used learning from demonstration techniques (Ontañón et al. 2009) and crowdsourcing (Breazeal et al. 2013) to gather instances, but the acquisition process was separated from the actual system deployment. Since instance-based methods respond to a given query by combining information from stored data, the quality of retrieved instances depends on how well the system's knowledge base covers the task space. Though there are various ways to measure the quality of retrieval results, querying the system for better instances around the query instance, especially in real time, is a complex problem. With our proposed approach, the teacher is able to interrupt the robot's behavior and provide necessary instances at the moment learning is taking place, thus providing a means to utilize human input to cover the task space while continuously engaging the participant in the task. Within the IIBL framework, the user inputs keywords that they use to convey task knowledge to another person, such as object properties. These keywords, i.e., task features, are chosen based on the physical and perceptual capabilities of the robot. The features are associated with attributes such as data types, extraction and distance-measure methods. The nature of this instance-based method thus makes it possible for the system to accommodate different types and representations of task features and provides a framework for general task modeling.

Robot Learner Experiments

We have applied the proposed IIBL framework during our recent *Angry Darwin Expedition*, in which our robot, Darwin, learned to

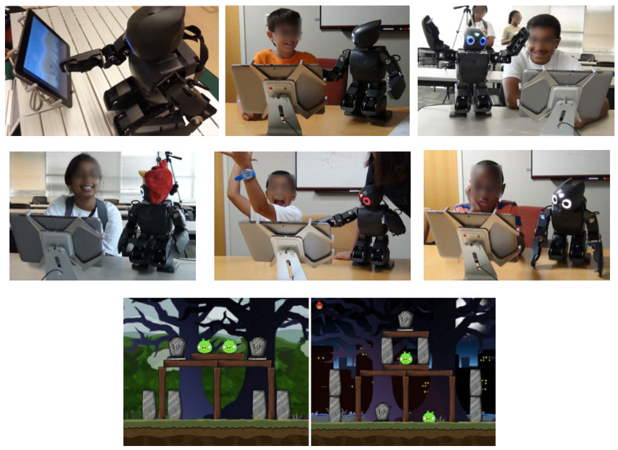

Figure 1. *Angry Darwin Expedition* was an effort to validate the capability of a robot learner in various interaction studies. The participants teach our robot, *Angry Darwin,* to play a game on a tablet while initiating social interactions as a teacher.

play a strategic game "Angry Birds" on a shared tablet workspace from various users (Figure 1). During a six-month period, over 130 people interacted with our robot learner including over 90 children, among which 33 participated in the formal experiment. The experiment consisted of two sessions that were recorded and post analyzed. In Session I, the participant played the game, without the robot learner, while the experimenter was present. In Session II, the participant was asked to teach the robot learner how to play the game. Session II consisted of two sub-sessions in which participants interacted with the robot learner using one of three learning strategies in varying orders. The instance-retrieval methods used by the robot were: Robot A (proposed IIBL), Robot B (traditional instance-based method using *k*-NN), and Robot C (random instance retrieval within the knowledge base). The social behaviors initiated by the participants were measured as the length of time when eye contact was made or when vocal- or gestural-interaction behaviors were observed. The aim of the interaction study was to compare the emergence of social behavior initiated by the participants when interacting with a person or a robot learner. We also conducted a pilot study with two children diagnosed with autism spectrum disorder (ASD), and compared their outcomes with a group of 19 typically developing children.

The average number of demonstrations (k = 4) given to each robot was: Robot A (m= 21.17, σ=6.44), Robot B (m= 29.17, σ =10.25), and Robot C (m= 24.15, σ=8.72). On average, participants provided 38% less demonstrations to Robot A than Robot B, while the average performance of Robot A was still better than that of Robot B by 28.48%. If a sufficient number of cases populate the problem space, Robot A and Robot B's performance will eventually converge. However, exploring all possible problems will increase the teacher's workload significantly. In the questionnaire asking when the participants stopped teaching each robot, majority of the participants answered "when Darwin clears each level several times" for Robot A (64%) and Robot B (61%), and "when Darwin stopped improving" for Robot C (52%). Participants also spent almost twice (90%) more time with Robot B than Robot A, and 26% more time with Robot B than Robot C. Participants spent more time instructing the robot when the robot was improving slower (Robot B), but quickly lost interest when the robot wasn't responding to the demonstrations (Robot C). Through these results, we observed that the participant's behavior changes, e.g., the amount of interaction and when to end an interaction, based on the robot learner's ability and performance.

In general, it was observed that the participants utilized other forms of natural interactions though the robot only could learn from physical demonstrations of the task. These interactions were then categorized into instructive and non-instructive interactions. On average, participants spent 5 minutes and 42 seconds with the experimenter and 24 minutes and 5 seconds with the robot playing the game, of which participants used 3.22% of the time initiating interactions with the experimenter and 34.81% with the robot learner. On a 5-point Likert scale, from strongly disagree (1) to strongly agree (5), post-experiment survey reports that the participants felt their robot was socially interacting with them (m=4.7); was socially communicating with them (m=3.72); thought Darwin was learning from them (m=4.33) similar to their friends does (m=4.01); and thought the robot enhanced their overall experience with the task (m=4.8).

From the pilot study with two children with ASD, the first participant (male, age 9) demonstrated close to average occurrences of social behaviors when the robot was present compared to the typically developing group. In Session I, the child initiated an interaction with the experimenter, which was 45% of the average time of the comparison group. In Session II, the amount of time spent initiating social behaviors toward the robot was 91% of that of the comparison group. The observed behaviors were: eye contact (28.23%), gestural interaction (12.17%), and vocal interaction (28.90%). The second subject (male, age 6) eagerly participated in the task but did not initiate any interaction with the experimenter or the robot. He spent most of the session observing the robot and murmuring to himself, but also talking to his parent about the robot (28.14%). Though his interaction wasn't aiming toward the robot, the robot's behavior mediated a conversation with his parent and demonstrated 73% of the average time of the comparison group.

Future work

As part of our future work, we are conducting research with children with cognitive development delays in collaboration with a play-therapy center. We are studying how the aspects of the robot (movement, sound, emotion expression) affect interaction. Findings from these studies will be reflected in a new robot design. We are also planning an evaluation with clinicians in regards to the feature-encoding interface. This evaluation will focus on addressing the issues of conveying the physical and perceptual capabilities of a robot platform to non-experts.

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