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Integrating Demonstration Learning and Q-Learning for Human-Robot Interaction in Pervasive Sensor Environments

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Abstract

In a ubiquitous sensory world, different types of services can be provided by robots regardless of where people are located because robots can provide them wherever they are moved to. Robots need to acquire reliable motion primitives like walking and object grasping so that they can perform a variety of useful tasks. It takes a long time to acquire movement primitives in a ubiquitous sensory world. The idea of machines picking up movement basics and engaging with people in computer simulations has been explored in a number of earlier works. One drawback is that there is no way to define motion primitives that a robot cannot perceive because of how it learns them. In this article, we craft a new method for learning interactions in simulated settings. To describe the motion primitives, we use demonstration-based learning to physically manipulate a robot. In addition, Q-learning can be used by a computer to pick up on social cues from people. The motor primitives were produced naturally in one trial using the suggested technique, and using them decreased the quantity of movement needed for a simulated person by about 25%.

Introduction

Robots can actively provide a wide range of services in ubiquitous sensory settings. After approaching humans and gathering knowledge about their routines, machines can provide services regardless of where people are located [1]. However, after a computer learns how to communicate with a person, the following issues may arise. In the first place, there are issues with learning time during interaction learning because a computer can't pick up on human behaviors very quickly. As a result, it's important to gain experience interacting with people without actually interacting with them. Second, because robots have limited perceptual capabilities, they pose a danger to humans if they engage with one another. Therefore, people need to have access to safety gear. Previous research has examined human-human contact learning in virtual settings, which can address the aforementioned issues [2-4]. Motor primitives for a virtual robot can be generated through demonstration-based learning and observation of a virtual person in virtual settings.

However, it is impossible to generate motion primitives that cannot be observed. Furthermore, the motor primitives of robots may vary from the motions of people, and it may not be feasible to execute the motor primitives produced for a robot due to these aesthetic variations. Therefore, advances must be made in the techniques used to create various motor primitives. Learning how to teach a robot movement primitive while simultaneously teaching it to communicate with people in a simulated world is an area that needs more investigation. In this article, we suggest a ubiquitous learning environment for learning interactions, wherein movement primitives are learned via example and executed via Q-learning.

The motor primitives are specified in the course of example learning techniques, making it possible for non-programmers to create motor primitives naturally. Using Q-learning, the freshly produced motor primitives can be executed without requiring any changes to the methods.

Connected Tasks In order for machines to communicate with people, many different kinds of learning systems are needed. This part provides a brief overview of the literature on the topics of motor-primitive learning and virtual-human contact. Robots can't do much of anything without mastering the foundational movement skills. Various motion primitives can lessen robots' repulsiveness. Several lines of investigation are currently underway to develop motion primitives for machines that look and feel more humanlike. A similar research, for instance, identified innate motor primitives for selecting the route of least resistance [5, 6]. These actions were generated by an evolutionary program. Motor primitives that did not optimize for the quickest route were eliminated through evolution, and new motor primitives were created in their place. Use of demonstration-based learning is another method [7-9]. Algorithms that learn from demonstrations memorize and then analyse a set of motion primitives [7, 10] one at a time. Another method entails learning motor primitives by breaking down a sequence of motions into smaller, more manageable chunks [8]. In addition, a method was suggested that creates motor primitives in the form of a tree hierarchy [9, 11]. A robot performs the same motor primitive at the outset but various motor primitives in different stages, all within the same hierarchy structure. Planning algorithms are typically responsible for creating the motor primitives [12]. Applying planning formulas, however, is not without risk. The produced motor primitives are used in the definition of planning methods. Changes to the motion primitives necessitate updates to the planning methods used to implement them. Humans can specify motion primitives through demonstration-based learning, which eliminates the need for scripting. However, planning systems don't benefit from this feature. Therefore, methods that can be used despite modifications to the motion primitives are needed.

Human-robot interaction concept learned in a digital learning framework.

It takes a long time to acquire human relationships and the number of robot encounters is restricted in a ubiquitous sensory world. In order to maximize learning and thus enable high-quality implementation of muscle primitives, it is necessary to minimize the number of encounters. As can be seen in Figure 1, our method eliminates the need for encounters in real-world ubiquitous sensing settings by teaching them in a simulated setting. We describe a virtual person and a virtual robot as learning entities in a virtual ubiquitous sensory world. To work together, the simulated person behaves naturally and the virtual automaton uses motion primitives. By engaging with digital people, the computer can learn how to communicate with actual ones. The outcome of the learning process is then implemented in the physical automaton. In order to communicate with a real person, the actual robot uses movement primitives learned virtually.

Table 1: Approaches used in different stages of interaction learning by robots

Stage	Type of agent	Learning approach
Motor primitive learning	Virtual robot	Direct manipulation of a robot
Collaboration learning	Virtual robot	Interaction with a virtual human by Q-learning [13]

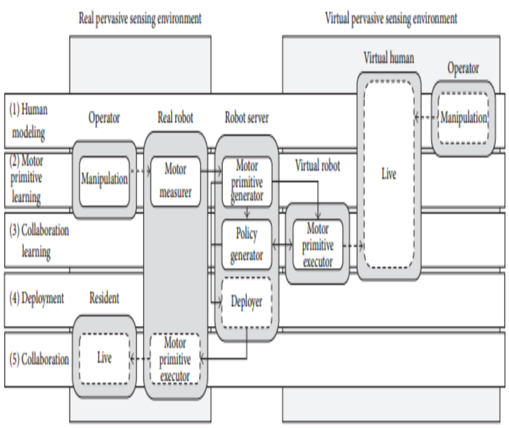

Figure 1: Framework for interaction learning.

Try Out Both Real and Virtual Setups

Ambient sensing systems. A Nao stood in for an actual automaton in our exercise. As can be seen in Figure 4, we also constructed a scale replica of a home that would have been appropriate for the Nao. There was a kitchen, a living area, and a bedroom in the sample home. The Nao picked up knowledge from talking to actual people. The Nao's mission was to bring the things an actual person needs to them. The Nao made an initial approach to the item after identifying it. Then it picked up the item, walked over to the actual human, and handed the item over to the human. The items in Table 2 were used in the tests. There were immovable items, and those that could be picked up, carried, and set down by a Nao or a person. Q-learning requires the state space to be specified in preparation. After capturing a photo with an omni camera mounted on the roof and splitting it into the grid shown in Figure 5, we used these values to represent the locations of the person and the automaton in this experiment. Each cell's breadth was determined by the Nao's girth. That's how we got to 50 individual cells. The person, the automaton, and the closest object's values were used to establish the boundaries of each condition. The simulated ubiquitous sensing environment used in this experiment was designed precisely like the actual pervasive sensing environment used in the experiment, as shown in Figure 6.

Thus, the simulated ubiquitous sensory world was an exact replica of the physical one in terms of both organization and scale. No face-to-face communication with actual people is needed. Any time a person is engaged in the learning process, the learning time issue arises, making it difficult to shorten the learning process. Accelerating interactions between a virtual person and virtual computer can further decrease training time. This is due to the fact that unlike actual humans and robots, simulated humans and robots do not have to perform muscle primitives at the same pace. Human modelling, motion basic learning, collaborative learning, implementation, and collaborative phases are all part of our method to interaction learning. Only the methods employed in Table 1 below, namely muscle primal learning and cooperation learning, are proposed in this study. In the human modelling phase, humans direct a synthetic human to carry out present movement primitives in order to make it behave like a human. By studying the human control process, the simulated people are taught to perform movement primitives. To teach the simulated robots how to move, humans take direct charge during the motor primitive learning stage, after which the robots come up with their own motor primitives on their own. The simulated robot then uses the acquired movement primitives in a simulated human

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interaction. Through this practice, the simulated computer acquires the skills necessary to assist people. The outcomes of motion primitive creation and interaction are then implemented in a physical robot that can engage in natural human contact.

Figure 2: Model house as a pervasive sensing environment.

Table 2: Objects used in the experiments.

Location	Object	Object type
Kitchen	Cup	Movable object
	Kettle	Movable object
	Chair	Movable object
	Kitchen table	Static object
	Stove	Static object
Living room	TV table	Static object
	TV (assumed)	Static object
	Couch	Static object
	Remote controller	Movable object
	Newspaper	Movable object
Room	Bed	Static object

figure 3: Grid environment of the real pervasive sensing environmint used for interaction learning. sensing environment.

Objects were also deployed in the same way as the real pervasive sensing environment. We utilized two virtual agents as a virtual human and a virtual robot.

Interaction Learning Results

(a) Scenario where a virtual human life alone is as follows:

(I) a virtual human sleep,

(ii) the human wakes up on a bed,

(iii) the human walks to a couch,

(iv) the human sits on the couch for a while,

(v) the human stands up on the couch,

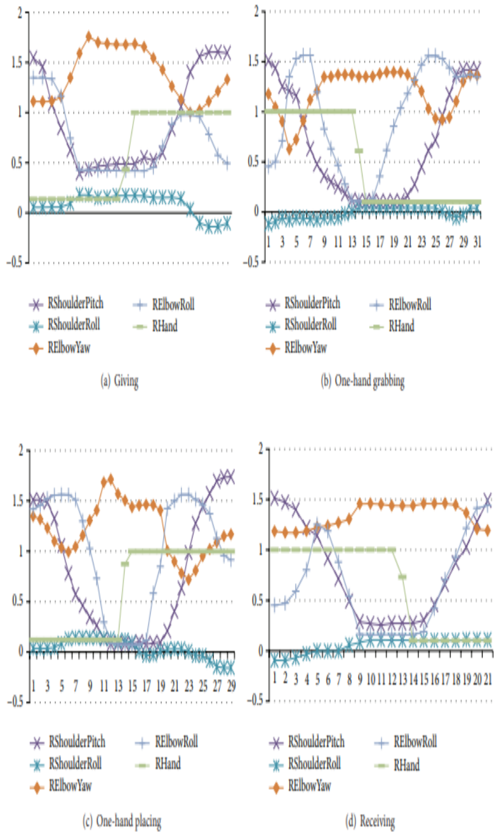

Figure 4: Four motor primitives produced for a robot.

(vi) the human walks to a newspaper,

(vii) the human picks up the newspaper, and

(viii) the human reads the newspaper.

(b) Scenario where a virtual robot provides services is as follows:

(I) a virtual human sleep,

(ii) the human wakes up on a bed,

(iii) the human walks to a couch,

(iv) while the human sits on the couch:

(1) a virtual robot walks to a newspaper, and

(2) picks up the newspaper.

(v) when the human stands up on the couch:

the robot walks to a virtual human, and

(2) gives the newspaper.

(vi) the human receives the newspaper, and

(vii) the human reads the newspaper.

Figure 5 shows the accumulated rewards according to the increase in the amount of interaction learning. After 14,000,

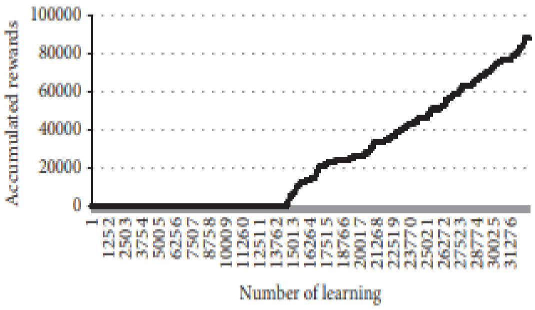

figure 5: A virtual robot delivers a newspaper to a virtual human.

The robot's ability to learn from experience increased. In the prior list (b), you can see how the simulated automaton modified the situation after learning from interactions. If a simulated person were to reside alone, it would pick up a copy of the newspaper on its own. If a simulated robot was present, however, the robot would take up the newspaper and deliver it to the synthetic person.

Conclusion

In this paper, we developed an approach to virtual pervasive sensing environment-based interaction learning where the operators taught motor primitives to a real robot by Manipurlating its arms directly. The learned motor primitives were utilized by a virtual robot and executed to learn interactions with a human. The operators defined the motor primitives using manipulations, so various different types of motor primitives could be defined intuitively, which overcame the problems of previous approaches. The virtual human and the virtual robot used in our proposed method and Q-learning are suitable for single agentbased learning algorithms, so it is necessary to improve our proposed method by applying multi-agent-based Q-learning. A method is also required to allow a virtual robot to provide services to multiple virtual humans. Finally, an approach will be developed to facilitate the application of the learned interaction results to a real robot.

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