A Case-Based Framework for Task Demonstration Storage and Adaptation

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Abstract. We address the problem of imitation learning in interactive robots which learn from task demonstrations. Many current approaches to interactive robot learning are performed over a set of demonstrations, where the robot observes several demonstrations of the same task and then creates a generalized model. In contrast, we aim to enable a robot to learn from individual demonstrations, each of which are stored in the robot's memory as source cases. When the robot is later tasked with repeating a task in a new environment containing a different set of objects, features, or a new object configuration, the robot would then use a case-based reasoning framework to retrieve, adapt, and execute the source case demonstration in the new environment. We describe our ongoing work to implement this case-based framework for imitation learning in robotic agents.

Keywords: Case-based agents, imitation learning, robotics

1 Introduction

Imitation is an essential process in human social learning and cognition [11, 10]. Imitation learning occurs when a learner observes a teacher demonstrating some action, providing knowledge of (i) how the action was performed and (ii) the resulting effects of that action. This interaction-guided learning method allows us to learn quickly and effectively. As a result of its importance in human cognition, it follows that imitation learning has become an area of increasing focus in interactive robotics research as well.

The goal of *Learning from Demonstration* is to enable imitation learning in robots through interactive demonstrations, provided through methods such as teleoperation or kinesthetic teaching [1, 2]. Regardless of which demonstration method is used, the following process is often used. First, the human teacher provides several demonstrations of a skill. Between demonstrations, the teacher may adjust the environment such that the skill is demonstrated in a variety of initial configurations. The robot then creates an action model which generalizes over the provided demonstrations. Lastly, the robot applies the generalized action model to plan a trajectory which is executed in a new environment.

However, a challenge of this process is that the resulting action model is dependent on the number of demonstrations that were provided for that particular task. We also assume that the robot has been exposed to enough variations of the initial configuration such that its generalized model can be applied to a wide range of related initial configurations. As such, the generalized model is restricted to application in environments which are similar to those demonstrated.

We describe our preliminary work toward defining an alternate approach to imitation learning in robotics, one which takes a *case-based* approach in which the robot stores demonstrations *individually* in memory. We define a case-based framework which enables the full imitation learning process, from observing a task demonstration to transfer and execution. We also define a case representation which encodes task demonstrations for storage in source case memory.

2 Related Work

Case-based reasoning has been used to address the problem of transfer in robotics domains. Floyd, Esfandiari & Lam [7] describe a CBR approach to learning strategies for RoboCup soccer by observing spatially distributed soccer team plays. Their approach represents each case as an encoding of a single agent's perception and resulting action at a given time. Thus, they transfer the behavior of an agent when it perceives a situation similar to that of the observed agent. More recently, Floyd & Esfandiari [6] describe an approach for case-based learning by observation in which strategy-level domain-independent knowledge is separated from low-level, domain-dependent information such as the sensors and effectors on a physical robot. Ontañón et al. [8] describe their approach to observational learning for agents in real-time strategy games. They use a case-based approach to online planning, in which agents adapt action plans which are observed from game logs of expert demonstrations.

While these approaches do address knowledge transfer for robotic and simulated agents, they primarily operate over input and output represented at a higher level of abstraction, such as actions at a strategic level. The goal of our work is to enable transfer to generate action at a lower level of control and in response to real-world perceptual input, where we transfer the demonstrated action trajectory used to achieve a task. We expand on our previous work [3] describing a case-based approach to interpretation and imitation in robotic agents. We discussed two separate processes: (i) interpreting new skill demonstrations by comparing it to previously observed demonstrations using a case based process (further described in [5]), and (ii) a related process for imitating a task demonstration. This paper expands on the latter process, case-based imitation.

We previously provided a general outline for imitation in [3] in which four steps occur: representation of the task demonstration at multiple levels of abstraction, retrieval of the most relevant source case from memory, adaptation of the source case to address the target problem, and execution of the adapted case in the target problem. In this paper, we describe our more recent work providing (i) a revised, complete process of imitation beginning with observation

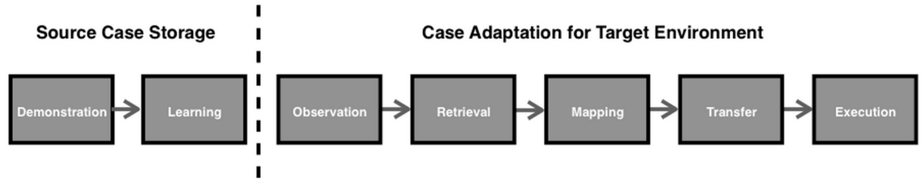

Fig. 1. Case-Based Process for Task Demonstration Transfer

of the task demonstration and ending with task transfer and execution, (ii) a *Mapping* step which bridges the gap between the *Retrieval* and *Transfer* steps, and (iii) a revised case representation for storing task demonstrations (iterating on preliminary work introduced in [4]).

3 Approach Overview

We have revised our case-based approach to transfer (originally summarized in [3]) to consist of two separate processes, as shown in Figure 1: the *Case Storage* process in which the robot receives demonstrations of a task and stores each demonstration as a case in source memory, and a *Case Adaptation* process which is used at a later time when the robot is asked to repeat a task in a target environment.

3.1 Why a CBR approach?

Our eventual goal is to enable transfer for imitation learning in scenarios such as the following. A human teacher guides the robot to complete a task such as scooping the contents of one container into another. During the demonstration, the robot records the demonstrated trajectories and object features. At a later time, the robot is asked to repeat the *scooping* task, but in a new, *target* environment. Thus, the robot must use a different set of object features to parameterize and execute the *scooping* task than those observed in the original, *source* environment. Next, the robot transfers its representation of the *scooping* task to accommodate for the differences between the source and target environments. The transferred task representation is then executed in the target environment.

Rather than generalize over a set of demonstrations as in current Learning from Demonstration methods (surveyed in [1, 2]), using a case-based approach allows us to: (1) operate under the assumption that the human teacher will provide a limited number of demonstrations, (2) represent demonstrations as individual experiences in the robot's memory, and (3) utilize a complete framework for transferring skill demonstrations, which includes the steps of retrieving, analyzing, transferring, and executing a relevant *source case* demonstration in an unfamiliar, *target environment*.

3.2 Case Storage Process

Demonstration and Learning We have implemented the first step in the *Case Storage* process, where the robot records and stores each task demonstration as a source case in memory. We define each case as the tuple $C = <L, D, T, O, S_i, S_f>$, where:

- L represents the label of the task which was demonstrated, e.g. "scooping".
- D represents the set of action models which encode the demonstrated motion, represented as Dynamic Movement Primitives as defined in [9].
- T is the set of parameterization functions which relate the set of action models to the locations of objects in the robot's environment. For example, a parameterization function may be used to represent how the robot's hand must be located above a bowl prior to completing a *pouring* action.
- O is the set of *salient* object IDs which are relevant to the task.
- S_i and S_f are the initial and final states, respectively, which represent the set of objects observed in an overhead view of the robot's environment.

3.3 Case Adaptation Process

At a later time, the robot may be asked to repeat the task in a new, target environment. We are currently implementing the Case Adaptation process shown in Figure 1.

Observation will begin when the robot is asked to address a target problem. We assume that the robot has been provided a relevant source case which it can retrieve from memory to address the given target problem. The robot will then observe the target environment by viewing the objects located in the table-top environment using an overhead camera. This will provide it with the target case's initial state S_i.

Retrieval must be performed to select a source case from memory containing the demonstration that is most relevant to the current target problem. Case retrieval will prioritize (i) similarity of task goals, (ii) similarity of salient objects, and finally, (iii) similarity of initial states. Once a relevant source case has been retrieved, the *Mapping* step must encode the differences between the source and target environments. This mapping will be later used to transfer the source case such that differences in the target environment are addressed.

Given a source case and mapping which encodes the differences between the source and target cases, the *Transfer* step adapts the source case. We take a similarity-based approach to transfer, where we consider the similarity between the source case and target environments when defining transfer processes. As we encounter transfer problems in which the source and target problems become less similar, the source case is transferred at a different level of abstraction, such that only high-level features of that case are transferred. The adapted case is then *executed* in the target environment.

We have implemented three methods which implement the *Transfer* step, each of which operates by transferring the source case at a different level of abstraction. Once the source case has been transferred, it is used to plan and execute a new action trajectory. In preliminary experiments, we have evaluated each method separately such that we selected the level of abstraction at which transfer occurred in each target problem. These experiments have shown us that by changing the level of abstraction at which a case is transferred, a robot can use a single source demonstration to address target environments of varying similarity to the source environment.

4 Future Work

We have implemented the Case Storage process and the last two steps of the Case Adaptation process, the *Transfer* and *Execution* steps. Currently, we manually provide the robot with the most relevant source case demonstration and a mapping between objects in the source and target environments. Thus, our next steps are to identify a method for autonomously determining this object mapping. Furthermore, future work will involve defining a process for identifying and retrieving an appropriate source case demonstration that is most applicable to a given transfer problem.

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