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Programming-by-Demonstration of reaching motions—A next-state-planner approach

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ABSTRACT

This paper presents a novel approach to skill acquisition from human demonstration. A robot manipulator with a morphology which is very different from the human arm simply cannot copy a human motion, but has to execute its own version of the skill. When a skill once has been acquired the robot must also be able to generalize to other similar skills, without a new learning process. By using a motion planner that operates in an object-related world frame called hand-state, we show that this representation simplifies skill reconstruction and preserves the essential parts of the skill.

1. Introduction

This article presents a method for imitation learning based on fuzzy modeling and a next-state-planner in a Programming-by-Demonstration (PbD) framework. For a recent comprehensive overview of PbD, (also called Learning from Demonstration) see [1]. PbD refers to a variety of methods where the robot learns how to perform a task by observing a human teacher, which greatly simplifies the programming process [2–5]. One major scientific challenge in PbD is how to make the robot *capable* of imitating a human demonstration. Although the idea of copying human motion trajectories using a simple teaching–playback method seems straightforward, it is not realistic for several reasons. Firstly, there is a significant difference in morphology between the human and the robot, known as the correspondence problem in imitation [6]. The difference in the location of the human demonstrator and the robot might force the robot into unreachable parts of the workspace or singular arm configurations even if the demonstration is perfectly feasible from human viewpoint. Secondly, in grasping tasks the reproduction of human hand motions is not possible since even the most advanced robot hands cannot match neither the functionality of the human hand nor its sensing capabilities. However, robot hands capable of autonomous grasping can be used in PbD provided that the robot can generate an appropriate reaching motion towards the target object, as we will demonstrate in this article.

In this article, we present an approach to learning of reaching motions where the robot uses human demonstrations in order to collect essential knowledge about the task. This knowledge, i.e., grasp-related object properties, hand–object relational trajectories, and coordination of reach and grasp motions is encoded and generalized in terms of models of *hand-state space* trajectories. The hand-state components are defined such that they are perception invariant and defines the correspondence between the human and robot hand. The hand-state representation of the task is then embedded into a next-state-planner (NSP) which enables the robot to perform reaching motions from an arbitrary robot configuration to the target object. The resulting reaching motion ensures that the robot hand will approach the object in such a way that the probability for a successful grasp is maximized.

In the literature on PbD different methods and tools to cope with problems like modeling and recognition of human and robot motions, and the performance of demonstrated skills and grasps have been presented. According to [7] these tools include Artificial Neural Networks (ANNs), Radial-Basis Function Networks (RBFs), Fuzzy Logic, or Hidden Markov Models (HMMs). On the other hand, several examples on a comparison of fuzzy methods with other methods like GMM and HMM can be found. For example, in a study by Hanson et al. on tools for the design of car interiors, regarding human-like movements with respect to object, environment and personal characteristics, the superiority of fuzzy clustering and modeling over GMM with regard to accuracy could be shown [8].

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Nevertheless, not a use of one single method for all tasks alone will lead to a full success, but the combination of these methods will be the best way to tackle the problems arising with PbD. In our approach, the trajectory models are built on the basis of fuzzy techniques which are most advantageous for quasi-continuous trajectories used in our case. Compared to other methods like Gaussian Mixture Models (GMM) this method allows a more effective modeling on the basis of which a simple but successful recognition of human and robot motions can be realized [9].

An NSP is a trajectory planner that plans one step ahead from its current state. This contrasts to traditional robotic approaches which plan the entire trajectory in advance. A few of the first researchers to use an NSP approach in imitation learning were Ijspeert et al. [10], where they encode the trajectory in an autonomous dynamical system with internal dynamic variables that shapes a "landscape" used for both point attractors and limit cycle attractors. For controlling a humanoid's reaching motion, Hersch and Billard [11] considered a combined controller with two controllers running in parallel; one controller acts in joint space, while the other one acts in Cartesian space. To generate reaching motions and avoiding obstacles simultaneously Iossifidis and Schöner [12] used attractor dynamics, where the target object acts as a point attractor on the end-effector. The end-effector as well as a redundant elbow joint avoids an obstacle as the arm reaches for an object.

In our approach, a human demonstration guides the robot to grasp an object. Our use of an NSP differs from previous work [10–12] in the way it combines the demonstrated path with the robots own plan. The use of hand-state trajectories distinguishes our work from most previous work on imitation. According to [10], most approaches in the literature use the joint space for motion planning while some other approaches use the Cartesian space. Moreover, we consider skill transferring from human to industrial manipulator, where the correspondence is less, compared to the scenario with skill transfer from human to a humanoid robot as described by [10,11]. We show that human to robot skill transfer is possible, despite the different morphologies (Section 5). We hypothesis that skills built from own experience can be used to further improve the performance since these skills are better adapted to the robot's own morphology than skills modeled from observing the human demonstrator.

To illustrate the approach we describe five scenarios where human demonstrations of goal-directed reach-to-grasp motions are reproduced by a robot. Specifically, the generation of reaching to grasp motions in a pick-and-place tasks is addressed. In the experiments we test how well the skills perform the demonstrated task, how well they generalize over the workspace, how they perform in the presence of a perturbation and how skills can be adapted from self-execution. The contributions of the work are as follows:

1. We introduce a novel next-state-planner based on a *fuzzy modeling* approach to encode human and robot trajectories.
2. We apply the *hand-state concept* [13] to encode motions in hand-state trajectories and apply this in PbD.
3. The combination of the NSP and the hand-state approach provides a tool to address the *correspondence problem* resulting from the different morphology of the human and the robot. The experiments shows how the robot can generalize and use the demonstration despite the fundamental difference in morphology.
4. We present a performance metric for the NSP, which enables the robot to evaluate its performance and to adapt its actions to fit its own morphology instead of following the demonstration.

The combination of fuzzy models and Q-learning has been proposed by others (see for example [14,15]). Typically, the main purpose for this combination is to use some fuzzy modeling technique to approximate the value function in the action selection process, which otherwise will suffers from the well-known curse of dimensionality. In this paper fuzzy modeling is used for trajectory encoding, while the action selection (Q-function) used later on is approximated using Locally Weighted Projection Regression [16].

2. Learning from human demonstration

The main idea in PbD is to show the robot what to do by demonstrating the task, and thereby letting the robot programmer (here called demonstrator) create an executable robot program in a simple manner. In our case, the demonstrator shows the task by performing it in a way that seems to be feasible for the robot. This means that we assume the demonstrator to be aware of the particular restrictions of the robot. In this work we consider only the body language of the demonstrator, i.e., the approach is entirely based on proprioceptive information. A human demonstration is interpreted under two assumptions: the type of tasks and grasps that can be demonstrated are *a priori* known by the robot; only demonstrations of power grasps (e.g., cylindrical and spherical grasps) are considered, which can be mapped to – and executed by – the robotic hand.

2.1. Interpretation of demonstrations in hand-state space

To enable the robot to interpret human goal-directed motions in the same way as its own motions, we aim to mimic the functionality of the Mirror Neuron System (MNS) model of [13]. The hand-state hypothesis from the MNS model, is used to create the necessary associations between human and robot reaching and grasping. Following the ideas behind the MNS model, both human and robot motions are represented in hand-state space. A hand-state trajectory encodes a goal-directed motion of the hand during reaching and grasping. Thus, the hand-state space is common for both the demonstrator and the robot and preserves the necessary execution information. Therefore, a particular demonstration can be converted into executable robot code, furthermore, experience from multiple demonstrations is used to control and improve the execution of new skills. So, when the robot tries to imitate an observed reach and grasp motion, it has to move its own hand so that it follows a hand-state trajectory similar to the demonstrated one. If such a motion is successfully executed by the robot, a new robot skill is acquired. Seen from a robot's perspective, human demonstrations are interpreted as follows.

If hand motions with respect to a potential target object are associated with a particular grasp type G_i, it is assumed that there must be a target object that matches the observed grasp type. In other words, the object has certain grasp-related features, also called *affordances* [13], which makes this particular grasp type appropriate. The position of the object can be retrieved by a vision system, or it can be estimated from the grasp type and the hand pose, given some other motion capturing device. For each grasp type G_i, a subset of suitable object affordances is identified a priori and learned from a set of training data. In this way, the robot is able to associate observed grasp types G_i with their respective affordances A_i.

It should be noted that the definition of the term *affordance* in our work is the same as in the work of Oztop and Arbib [13], which differs from many other works in robotics see Sahin et al. for an overview [17]. Typically, affordances refer to visual object features which link objects to particular actions or action possibilities. That is, the affordance can tell what action can be applied to an object but not how it can be applied. In our approach, the purpose of the affordance is to link a particular motion primitive to an arbitrary object that can be handled by this primitive. Therefore, we use the affordance to define the hand-state variable which contains all information need to execute a motion primitive. Consequently,