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Teaching and learning of robot tasks via observation of human performance

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Abstract

Within this paper, an approach for teaching a humanoid robot is presented that will enable the robot to learn typical tasks required in everyday household environments. Our approach, called Programming by Demonstration, which is implemented and successfully used in our institute to teach a robot system is presented. Firstly, we concentrate on an analysis of human actions and action sequences that can be identified when watching a human demonstrator. Secondly, sensor aid systems are introduced which augment the robot's perception capabilities while watching a human's demonstration and the robot's execution of tasks respectively. The main focus is then layed on the knowledge representation in order to be able to abstract the problem solution strategies and to transfer them onto the robot system.

Keywords: Robot tasks; Programming by Demonstration; One-Shot-Learning

1. Introduction

Service robots, which are supposed to assist humans in their daily household work, must be adaptable and flexible. They must be adaptable on the one hand to the individual requirements and needs and on the other hand to the user's environment. As each household environment is different depending on its geometric setup, its provided functionality and the requested tasks to be performed by the robot, ready-made programs will not be able to cope with such environments. So, flexibility will surely be one of the most important requirements for the robot's design. It must be able to navigate through a changing environment, to adapt its recognition abilities to a particular scenery and to manipulate a wide range of objects. Furthermore, it is extremely important for the user to easily adapt the system to his needs, i.e. to teach the system what to do and how to do it. We think that the only approach that satisfies the latter condition are systems that automatically acquire relevant information for task execution by observation and multi-modal dialogues.

Learning of action sequences or operation plans is an abstract problem, which supposes a modeling of cognitive skills. When learning complex action sequences, basic manipulation skills or controlling techniques are not investigated. In fact, the aim is to generate an abstract description of the demonstration reflecting the user's intention and modeling the problem solution as optimal as possible. Robot independence is an important issue because it would allow to exchange of robot programs between robots with different kinematics. Likewise, a given problem has to be suitably generalized, for example, distinguishing parameters specific for the particular demonstration and parameters specific for the problem concept. Both

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demand a certain insight in the environment and the user's performance.

Obviously, systems providing this functionality require powerful sensor systems to gather as much information as possible by observing humans behavior or processing explicit instructions like commands or comments. They need a methodology to transform observed information for a specific task to a robot independent and flexible knowledge structure, and actuator systems using this knowledge structure to generate actions that will solve the acquired task in a certain target environment.

The following article shows how a robot may be programmed based on a human demonstration. After presenting related approaches a classification of typical human actions is given in Section 3. Compared to previous publications, e.g. [6], we will concentrate on the recognition of demonstrated tasks, the knowledge representation and the applicability for robot systems in Section 4. In order to observe human actions and their effects in the environment we use a training center which is equipped with additional sensor systems to obtain all relevant data for the learning process. This is presented in Section 5 together with the execution environment where tasks are performed by the robot.

2. State of the art

Several programming systems and approaches based on human demonstrations have been proposed during the past years. Many of them address special problems or a special subset of objects only. An overview and classification of the approaches can be found in [4,16].

Basis for the mapping of a demonstration to a robot system are the task representation and task analysis. Often, the analysis of a demonstration takes place observing the changes in the scene. These changes can be described using relational expressions or contact relations [9,14].

Issues for learning to map action sequences to dissimilar agents have been investigated in [1]. Here, the agent learns an explicit correspondence between his own possible actions and the actions performed by a demonstrator agent by imitation. To learn correct correspondences several demonstrations of the same problem are necessary for the general case. In [13] the authors concentrate on the role of interaction during task learning. They use multiple demonstrations to teach a single task. After generalization they use the teacher's feedback to refine the task knowledge.

For generalizing a single demonstration mainly explanation-based methods are used [8,11]. They allow for an adequate generalization taken from only one example (One-Shot-Learning). Approaches based on One-Shot-Learning techniques are the only ones feasible for end users since giving many similar performing examples is an annoying task.

A physical demonstration in the real-world can be too time-consuming and may not be mandatory. Some researchers rely on virtual or iconic demonstrations [3]. The advantage of performances in a virtual world is that here manipulations can be executed that would not be feasible in the real-world because of physical constraints. Furthermore, inaccuracies of sensor-based approaches do not have to be taken into account. This way, in existing approaches object poses or trajectories [19,20] and/or object contexts [14,17] are generalized in an appropriate way. A physical demonstration however is more convenient for the human operator. Iconic programming starts at an even more abstract level. Here, a user may fall back on a pool of existing or acquired basic skills. These can be retrieved through specific cues (like icons) and embedded in an action sequence. The result of such a demonstration of operator sequences can then be abstracted, generalized and summarized as new knowledge for the system. An example can be found in the skill-oriented programming system SKORP [3] that helps setting up macro-operators out of actuator or cognitive elementary operators interactively.

Besides a derivation of action sequences from a user demonstration direct cooperation with users has been investigated. Here, user and robot reside in a common work cell. The user may direct the robot on the basis of a common vocabulary like speech or gestures [18,21]. But this allows for rudimentary teaching procedures only.

3. Classification of human demonstrations

Within the framework of *Programming by Demonstration*, the basis for successfully mapping task

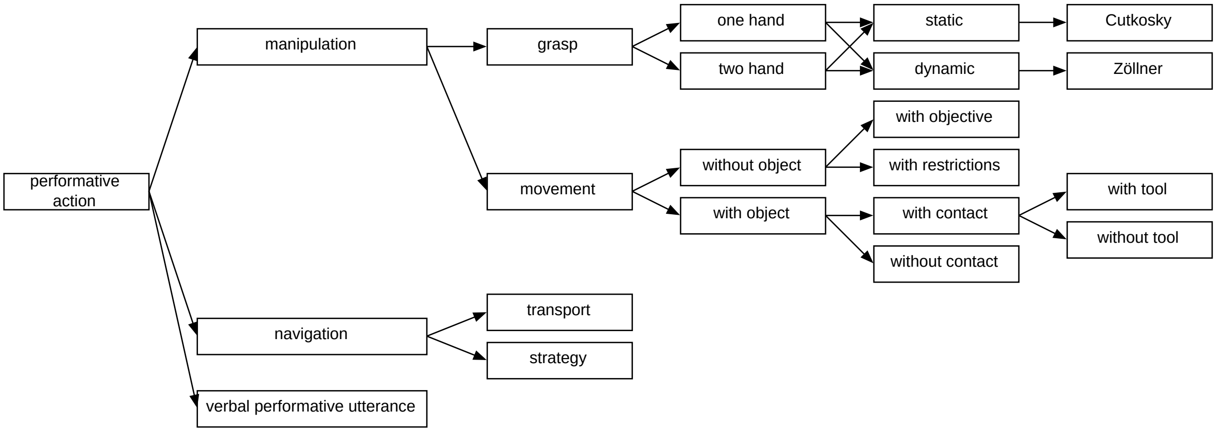

Fig. 1. Overview on user actions classified by purpose (only performative action classification is shown).

solutions from a human to a robot system is the ability of the programming system to recognize and to interpret human actions. In cognitive psychology, human activity is characterized by three features [2]: *Direction*, *Decomposition* and *Operator selection*.

It is important to know that cognition is mainly taken to be directed as well. Furthermore, humans tend to perceive activity as a clearly separated sequence of elementary actions. The most useful information for interpreting such a sequence is to be found in the transition from one elementary action to another [12].

For ease of use of a programming system, the set of supported elementary actions should be derived from human interaction mechanisms. Based on the purpose that is being aimed at by the application of operators, a categorization into three categories seems to be appropriate: *performative* actions, *commenting* actions and *commanding* actions.

The identified categories may be rolled out by the modality of their application (see Fig. 1). For a deeper discussion of commenting and commanding actions, we refer to previous publications [7,10,15]. In this paper, we will focus on performative actions. For teaching an action sequence to a robot system, this is the most important type of action.

4. Programming by Demonstration

The *Programming by Demonstration* approach consists of several stages starting with the user's demonstration, building a generalized representation of the segmented data and finally executing the gathered task knowledge. The whole cycle is described in detail in [6].

This section discusses questions concerning background knowledge required for understanding human demonstration, for abstraction and representing certain fulfilled tasks and for transferring demonstrations across different embodiments into a robotic system. To meet these requirements the knowledge representation is divided into different levels with varying degrees of complexity and constraints. The following subsections describe these levels and discuss in detail the models being used including implicit and explicit background knowledge with respect to task-specific constraints.

It has to be pointed out that we are not interested in teaching specific skills, e.g. specific finger joint angles for a certain type of grasp, since we assume that these basic skills are already implemented on the robot system. In fact learning is performed on the level of tasks.

As an illustrative example we selected the scenario 'A human gets a bottle from a refrigerator'. It should lead through this chapter to illustrate and to motivate the proposed methods. The following topics will be discussed:

- Understanding the fulfilled task and the human intention.
- Learning and representing a demonstrated task.
- Mapping and executing learned tasks with the robot system.

Fig. 2 illustrates the proposed information flow from the human demonstration to explicit robot instructions.

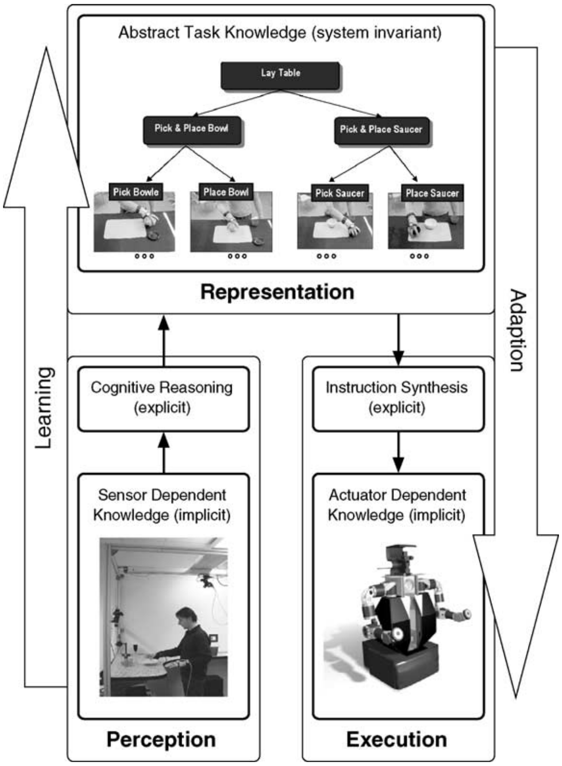

Fig. 2. Transfer of a human demonstration to a robotic target system.

4.1. Background knowledge for sensor interpretation

Starting with the above scenario, the sensor system observing human activity must be able to detect actions like opening a door, analyzing the contents, grasping an object, tracking items, etc. Therefore vast sensory input is used combining dedicated sensors like data gloves, magnetic trackers and stereo vision for collecting data from the demonstration (see Fig. 4 for details). Afterwards a transformation from sensor readings to adequate features allowing reasoning on the performed actions must be performed. The main issue is the determination of relevant features like hand positions, speed, type of grasp associated to specific actions. Obviously, this depends on the respective sensor characteristics. That is, for each sensor a context-dependent model based on background knowledge has to be provided. Triggering the feature extraction by determining the right context from previous sensor data leads to an incremental approach which can only be handled by introducing higher cognitive understanding into the system.

In terms of the above example three major contexts are distinguished: '*opening the refrigerator door*', '*extracting the bottle*' and '*closing the door*'. Each of these steps consists of more elementary operations like hand move types and different grasps. Analyzing the background knowledge being used, extraction of general features requires an implicit sensor model, determination of the context estimation, actual sensory data and transformation rules.

The selection of elementary operators is triggered by a rule-based system enabling multiple hypotheses. Hereby the knowledge being used consists of generally applicable context information. In our case this context information is determined by deciding whether an object is grasped, by analyzing the world state in terms of geometric relations and by asserting roles between objects and hands. Finally finding preconditions for applicability of elementary operators obtained by analyzing the current world model will close a loop to context determination and hence will lead to resolve the generated hypothesis. Since autonomous extraction of user's intention cannot be guaranteed, interaction based on speech and gestures is included in the decision process. Here another issue consists in determining whether a gesture or a manipulation action is performed. This issue can be solved by using speech to clarify the context and by separating gestures and manipulation actions using tactile sensors of the data glove. Hereby the restriction is made that no (external) forces are applied to the hand executing a gesture. Summarizing, our approach relies mainly on the categorization of elementary operators. That is, elementary operator types and characteristics constitute the limitation of the system. In the current state, for manipulation tasks the following restrictions can be identified: all objects have to be modeled and categorized and at least one hand has to grasp (touch) an object. Under these conditions even if one elementary operator is missing this can be detected in order to start a new interaction process for defining unknown elementary operators. For missing parts no generalization will be performed. Without generalization the execution will be a full imitation of the demonstrated task and thus the adaptation on different environments is very restricted.

4.2. Knowledge representation

A demonstrated task is represented by a sequence of elementary operators for each hand. In order to Build a vast task knowledge base, a flexible and extendable representation is needed, which allows the integration of new knowledge, reuse and combination of learned parts and representation of variations of one task. For meeting these requirements a formal grammar has been chosen. Elementary operators are defined as terminal symbols. The grammar rules are extended by each demonstration of a new task. Symbolic pruning through the grammar leads automatically to reusability of learned subtasks and the integration of alternatives. Since two-hand manipulations are considered, the context has to be integrated into the grammar rule building process, in order to maintain a maximum of information about the role of each hand during task execution. Moreover, high flexibility in terms of reusability of subtasks will be ensured using this type of formal grammar. Hereby the focus lays on the minimization of the coordination entities during the task. Consequently more information will be stored in context rules, containing the allocation and the role of each hand-specific subtask.

The introduced formalism over a grammar and the context information through pre- and post-condition for actions is a promising approach solving the problem of task representation. Reasoning and learning can be easily applied on this formalism. However efficiency of the formalism must be investigated when the number of production rules and the size of the alphabet (terminal symbols) increase.

4.3. Task examples and experimental setup

Stating our position in the current scientific workout, applicability of discussed sensors and the knowledge structure has been shown in several experiments [6]. Up to now, experimental results are limited to simple handling tasks with fixed cameras. Thus, we have created two scenarios to be able to demonstrate adaptability to more complex real-world tasks.

Within our experiments we want to concentrate initially on two typical activities that require high cognitive capabilities of the overall system and can easily be demonstrated by a human operator: *loading a dishwasher* and *taking out a bottle from a refrigerator*.

4.3.1. Loading the dishwasher

Actions that are going to be recognized are grasps for special dish types and target positions for the dishes within the box. This implicit information should be recognized and correctly interpreted by the system. Here, information about handled dishes and target positions are gathered by the two camera systems that have an overall view on the scenario. Grasp information will be provided from the sensor gloves. We will explicitly investigate two arm manipulations.

4.3.2. Take out bottles from the refrigerator

The second experimental task being planned is the grasping of objects within the refrigerator. Here, the overall learning task for the system will be: 'Take a bottle out of the fridge'. Obviously, the task can be divided into several sub-tasks like: 'Open the fridge', 'Grasp the bottle', 'Get the bottle out of the fridge', 'Close the fridge' and 'Put the bottle on the table in a stable position'. Fig. 3 illustrates that this task needs a flexible camera head that can position itself adequately to obtain a direct view inside the refrigerator. An optimal strategy for providing sufficient sensor information for correct task interpretation is one of the most interesting problems that is addressed within this experiment.

Within the experiments we want to develop a methodology for detecting typical tasks occurring in a common household. Our goal is to reduce background knowledge required for correct interpretation to a minimum in order to make the system also applicable for different deployments. Moreover, execution of the learned task will be shown in a real kitchen environment equipped with other sensor systems. Here, the scientific challenge will be to show that the acquired task solution knowledge is represented in a sensor- and actuator-independent way.

4.4. Applicability for robot systems

Learned task solution strategies are applicable to different robot embodiments. As pointed out previously, we assume that each robot target system endues a set of parametrized elementary operations. These elementary operations are strongly hardware dependent and either hard coded or assembled from a basic set of elementary sensor-controlled movements.

Fig. 3. Task examples: taking a bottle out of the fridge and putting dishes into the dishwasher box.

Assuming that a task solution strategy for a specific problem within a certain environment has been acquired from human demonstration, the question arises how to apply this knowledge for a robot system within the execution environment. In previous research we have developed a knowledge representation storing action sequences in a tree-like structure of macro-operators. Macro-operators represent the action sequence on a more abstract level and can be instantiated in new environments [6]. Leaf components of the macro-operator tree are elementary operators that store important information extracted from the demonstration in form of explicit parameters. These parameters might have the following form: type of handled objects, object-relative trajectories, grasp forces, interpolation points, etc. The top of Fig. 2 shows the simplified macro-operator 'laying the table' as an example.

When a macro-operator is instantiated in a new environment parameter values like handled objects and positions are substituted according to the current type and position of objects. Data about objects and their position can be gathered by evaluating sensor readings within the execution environment. Obviously, an active environment equipped with sensor systems can assist the robot system in finding correct object positions or types. Thus, our proposed kitchen environment with additional sensors at selected locations will enlarge the robot's cognitive capabilities in the execution case. Even if objects are not in the robot's sensor field, macro-operators can be instantiated when external sensors can detect objects within their area. Certainly this demands for a common world model which can be updated by the different sensor systems.

The next step will be to develop sensor system in the kitchen environment and on the robot system allowing to solve the tasks displayed in Section 4.3. Besides the cognitive abilities basic elementary operations for manipulation activities must be designed and implemented for the target robot systems ALBERT 2 (see Fig. 5) and ARMAR [5].

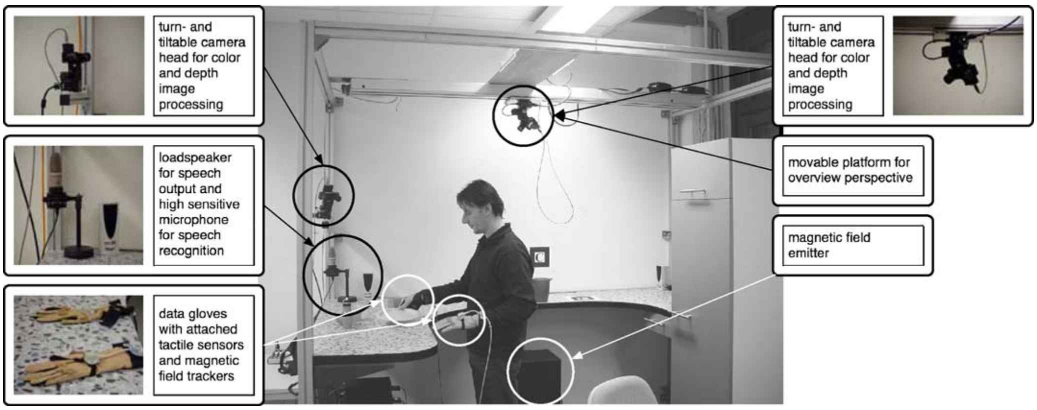

Fig. 4. Training center with installed sensor systems for observation of tasks (prototype).

Fig. 5. Robot assistant ALBERT 2 in execution environment (kitchen).

5. Training and execution center

The robot itself disposes of several sensors that realize external entities. However, those are limited when observing human activity and the environment in order to learn the performed task. Assuming that background knowledge about tasks and actions is limited, valuable information must be extracted by intimately observing the user during a demonstration. For real-world problems simplified demonstration environments will not lead to robot instructions that will be applicable in the general case. Therefore, we built up a dedicated environment, called *training center*, where user actions are performed to be learned by the robot. It is equipped with several systems, i.e. data gloves that allow to acquire precise data about the finger joint angle in order to classify specific grasps. Fig. 4 shows the training center with its different sensor systems.

Since our work is concerned with household environments and focuses on kitchen tasks, we have developed and set up a kitchen (see Fig. 5) as an execution center where devices may easily be operated by robots. The kitchen does not only consist of free space and manipulable objects but acts as supplementary extension of the robot's sensors and actuators.

6. Conclusion

In this article we presented an approach for teaching a robot new problem solution strategies. The tasks are demonstrated by humans in a training center which is equipped with several sensor aid systems to acquire as much information as needed to learn the performed tasks. Typical human actions were analyzed and a framework called *Programming by Demonstration* was implemented to segment and recognize these demonstrations. Macro-operators are a generalized structure to represent tasks as sets of elementary operators which are independent of specific robot systems.

Certainly, the proposed approach still leaves of some unanswered questions. In particular, type and attributes of elementary operators within the kitchen scenario need investigation. Since cognitive elements and the proposed knowledge representation have already been proven to work well for simple scenarios, one of the next steps will be to develop a generalized approach for mapping the introduced macro-operators onto robot systems. The mapping needs to identify and parametrize the basic skills implemented on the robot corresponding to the set of elementary operators of the macro-operator. So far it was done only onto a prototypical system to prove the concepts developed within the *Programming by Demonstration* framework.

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