Teaching Human Motion/Force Skills to Robots

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Abstract

In this paper we survey a number of methods for teaching human motion/force skills to robots. Since verbal description of a human skill could only provide qualitative guidelines for machine programming, several works were motivated to identify human skills analytically through the study of human teaching data. The key advantage of direct teaching by human demonstration is that the method is highly user-friendly; it requires no special knowledge of machine programming from the users, and it automatically extracts user intentions and strategies from task performance demonstrated by the users. From the early teaching/playback method to the recent methods of teaching sensory feedback laws, a historical perspective of the field of human skill teaching is given in this paper. Limitations and applicability of methods under review are discussed. Essential issues such as representation and identification of human skills as well as consistency of teaching information are addressed.

1. Introduction

Skill is the ability to perform a learned physical task and the intelligence to cope with uncertainties in the task based on sensory perception. Humans are uniquely capable of manipulating objects with skills to accomplish complex tasks. However, most people cannot describe precisely how they manipulate objects or interact with the environment. The detail of this ability and intelligence is invariably lost in the human subconscious, thereby making it highly difficult to quantify human skills and code them into machine instructions.

There have been a number of attempts toward developing human-like skills for robotic systems based on various approaches, such as task-level machine learning, teaching-by-showing, and the recently developed perception-action models of human skills. Task-level machine learning, such as the one proposed by Aboaf, et al., [1], requires the use of an accurate task model and an iterative learning process to build up machine intelligence. The result of learning is task specific, and its efficacy depends heavily on the model accuracy. In this paper, we focus on teaching methods for transferring human intentions, strategies, and skills to robots based on human demonstration. The key advantage of direct teaching of human skills is its user-friendliness in robot programming: it requires no special machine programming knowledge and allows factory floor workers to easily comprehend and effectively use sophisticated robots. In view of today's popular just-in-time strategy for manufacturing, this is particularly desirable for meeting small-batch, frequently changing task demands. In addition to this practical aspect, study of human skill is also essential to developing the theory of machine intelligence.

This paper gives a comprehensive discussion on the evolution as well as the state of the art in teaching motion/force skills to robots, and is organized as follows. In Section 2, a historical perspective on this area of study is given. In Section 3, essential issues in human skill acquisition, in particular, representation and quantification of tool/object manipulation skills are addressed. Research opportunities in teaching of human skills as well as their relevance to other fields of study are discussed in Section 4. Concluding remarks are given in Section 5.
2. Historical Perspective

The advancement in teaching human motion/force skills to robots has been parallel to the development of general approaches to robot control and programming. This is a natural result since only when the framework of robot control and programming was better established, did one realize more about what to look for in human demonstration that could be useful to robots. Lozano-Pérez [13] considered that general approaches to robot programming fell into three broad categories: teaching-by-showing, robot-level programming, and task-level programming. Here we review teaching methods for human skill transfer from a control engineering viewpoint, with the intention that these methods can be extended to a broader class of control system problems.

The progress of teaching methods for transfer of human motion/force skills in history can be roughly divided into the following stages: 1) teaching reference position trajectories, 2) teaching reference contact forces, 3) teaching feedback control laws, and 4) teaching task-level adaptive control laws. Using block diagrams typical for general control systems, these stages are depicted in Fig. 1. The historical background and the representative works in these stages are discussed in this section.

Teaching Reference Trajectories

In 1954, George C. Devol filed a U.S. patent for a new machine for part transfer, and he claimed the basic concept of teaching/playback to control the device. In principle, this teaching/playback method is a way to convey human intention in terms of position trajectory to robots by manually moving the robot arm through the desired points in work space. This method is highly user-friendly, and therefore has its widespread applications in the early industrial robots, such as pick-and-place, spray painting, and spot welding. However, by teaching/playback, only a single execution sequence of robot motion is specified; no sensory information has been incorporated into any feedback loop to account for uncertainties in the task environment. Clearly this deficiency limits this method to only simple tasks where uncertainty is minimal and no sensory feedback is needed.

Teaching Reference Forces

Robot force control began with telemanipulator and artificial arm control in the 1950s and 1960s [24]. In these applications, humans are directly involved in the control loops, through master-slave teleoperation or direct connections between joint motors and muscle electrodes. Therefore, a desired contact force with the task environment can be directly specified by the human operator.

For autonomous robots, Asada [2] presented the force teachable robot such that the robot can interact with external objects or environment with a prescribed contact force. In that implementation, the robot consisted of an arm and a hand with elastic fingers. The arm's movement was controlled with the position teaching/playback scheme, while the hand grasped objects with forces also taught by a human operator. The teaching of reference force is analogous to the conventional teaching of reference position, therefore it is also highly time-effective for robot programming. Hirzinger and Heindl [9] designed a force-torque-sensor ball which can be used to teach a robot reference paths for free motion in space and reference forces/torques when in contact with environment.

These two works represent the early research on direct teaching of position and force references to robots. Around the same time compliance and force controls in robotic systems were active research topics in the literature [7, 11, 20, 21]. The importance of specifying desired force-motion relations to robots interacting with task environment was clearly identified from these works. Hence, teaching of reference force-motion relations became the focus of study thereafter.

Teaching Feedback Control Laws

One of the main challenges in robot programming arises from uncertainties in task environment with which robots interact. Using sensory feedback in control,
robots can cope with a greater degree of uncertainty than without any sensing. The central issue in robot programming is therefore the design of a mapping (function) in the computer program that generates effective corrections in robot motions given a certain sensory feedback information \[18\]. Obviously this is related to design of feedback control laws for more general control problems.

In the context of teaching-by-showing, related research has been focused on extracting or recovering a mapping, from human demonstration data, that associates human responses with stimuli. This mapping, in an explicit mathematical or symbolic form, can then be used as an equivalent to a feedback control law in robot control systems. In addition to position information, common sensory signals in robotic applications also include force, vision, and tactile. For the case of force feedback, the feedback control law is taught so that a robot’s closed-loop behavior approximates a desired compliance or impedance, which defines an explicit relation between reaction force and robot motion. Hirzinger and Landzettel \[10\] showed that through on-line corrections induced by a human teacher via a force-torque-sensor-ball, a robot can be taught with a desired stiffness in its interaction with the environment. An associative memory was introduced to store a set of corresponding input (sensory signal) and output (robot motion) data such that during playback similar inputs mapped to similar outputs. The set of data used for training the associative memory was obtained during robot playback from human supervisor’s corrections. The human’s intention and strategy was conveyed to the robot only indirectly through a sensor ball. Since the human supervisor had not given any demonstration of his or her skill under a natural situation, the essential skill, such as the tool holding impedance in a deburring task, could not be extracted through this indirect teaching manner.

Asada and Izumi \[4\] presented a method for automatic program generation for the hybrid control of robots based on human teaching data. In principle, this is a direct approach to teaching a human operator’s skill in terms of force-motion relation in a task with force and motion constraints, since a human actually demonstrated the task performing skill in a natural manner during teaching. In \[3\], Asada and Asari applied this direct method to the case of deburring where the tool holding impedance of an experienced worker was identified from actual demonstrations.

For the case of using vision as the feedback signal, Kuniiyoshi, et al., \[15\] proposed a theory for visual recognition of human action sequences, which can be used for direct transfer of implicit task knowledge from human operators to robots. In this work, vision was used for both tracking movement of a human hand for program generation and for on-line feedback during task execution by the robot. Ikeuchi and Suehiro \[13\] devised a similar approach to automatic program generation for robot assembly task, and established the paradigm termed assembly plan from observation. Takahashi et al., \[23\] also presented a similar method for analyzing human assembly operations for use in automatically generating robot commands.

In \[25\], Yang et al., proposed a hidden Markov model (HMM) approach to human skill modeling and transferring. The HMM method treated its observation on a symbolic level, and that made the fusion of different sensory signals possible regardless of their physical meanings. With the framework of HMM, a most likely criterion is defined as a quantitative measure based on which the underlying skill can be uncovered from a set of human performance measurements. The concept of most likely performance makes it possible to use stochastic methods to cope with uncertainties in both human performance and environment. This has been demonstrated in \[25\] for teaching reference position trajectories. Application of the HMM method to transferring feedback control laws is currently under investigation.

So far, the teaching-by-showing method has been extended from teaching a position or force reference to a feedback control law that defines a mapping between sensory feedback inputs and robot motion outputs. This mapping, in most cases an associative memory, can be constructed based on human teaching data taken either from human-supervised robot motion or natural human motion (demonstrations). Although this mapping was readily applicable to robot control systems for generating human-like skillful motion, it was later realized that this mapping defined skill only under a certain restricted task condition. When the task condition varied substantially, the mapping relationship found in a human’s motion also changed accordingly. This problem was formulated by Liu and Asada with the framework of
adaptive control \[16, 17\], and teaching-by-showing was further generalized to transferring task-level adaptive control laws from humans to robots.

**Teaching Task-Level Adaptive Laws**

In \[16\], Liu and Asada considered skill as the generic ability to perform a class of tasks; that included association and generation of action strategies based on the perception of the task process state. They interpreted this perception-action cycle as a kind of adaptation capability in performing tasks with uncertainties and variations. In \[12\], Hogan observed a similar hierarchical structure in human movement production with a generic plan formulated at an abstract, task level and implemented at a more concrete continuous level. Using such models for human manipulation motion, the target skill to be taught to robots should include not only the control strategies for machine-level, continuous movement, but also the task-level adaptation law or a generic strategy planner. The hierarchical structure involving an inner feedback loop and an outer adaptation or strategy planner loop is depicted in Fig. 1.

In representing the task-level adaptive law, Liu and Asada \[17\] used a neural network to store the associative memory that related task-level process parameters to control strategy parameters. More specifically, using deburring as the example task in \[17\], the task-level process parameters referred to burr size and hardness and were identified based on a deburring process model, while the control strategy parameters included tool feedrate and tool holding compliance. In \[22\], a laser gap sensor was utilized for direct burr size measurement in identifying the associative memory from a human. Yang and Asada \[26\] employed a similar control structure in which a set of linguistic control rules was used to represent the associative memory obtained from human description. McCarragher \[19\] applied qualitative reasoning to interpret force signals generated by humans, and a discrete event controller for task-level decision making in an assembly process.

To recover adaptive control laws from human teaching data, as pointed out in \[16\], consistency is a critical issue in human skill study, particularly with the attempt to extract useful information from human motion for robot programming.

### 3. Elucidation of Human Skills

The common approach to human skill transfer for robot teaching has been generally focused on identifying a mapping (associative memory) that relates a human’s perception of task process state to some effective control actions. From the viewpoint of control engineering, this mapping may manifest as a certain feedback control law in a human’s motion, or as a high-level adaptive law that modifies feedback control to meet complex task environment. Within this framework, consistency arises as an issue which is critical to guarantee that every point in the perception space maps to at most one point in the control action space through the identified mapping. This is a necessary property for a skill since an inconsistent mapping would lead to unpredictable cases where a given process condition dictates two or more different (possibly conflicting) control actions. In such cases, it is impossible to decide which action to take based solely on data points in the input space. Fig. 2 shows an example of inconsistent relationship. A point defined by \(x\) in the input space corresponds to two distinct points in the output space, \(y_1\) and \(y_2\). Note that a valid mathematical mapping cannot be defined for this inconsistent relationship.

Since a human with a skill always make a clear control decision based on some perception inputs, it can be argued that the mapping from his/her perception space to his/her control action space is consistent. In fact, this mapping that mathematically characterizes a human skill is also a continuous function of some degree of smoothness. For the associative memory of a human, a small deviation \(|dx|<\delta\) in the perception variables will only lead to a small deviation \(|df(x)|<\epsilon\) in the control action.

![Fig. 2 Example of inconsistent relationship](image-url)
desired control command. Namely, a human slightly modifies an action in response to a small change in his/her perception [14]. Therefore, uniform continuity over the entire input space is often a desired property in modeling human behavior.

Given a set of human teaching data, the first step toward skill transfer is therefore to construct a perception space and a control action space such that the perception-action map is consistent and continuous. To this end, a quantitative method is needed to evaluate the consistency and continuity properties even before the mapping function is identified. Liu and Asada [16] devised a quantitative measure based on Lipschitz’s condition which is widely used in calculus for evaluating and defining continuity of analytical functions. Lipschitz’s condition states that a function $f(x)$ is uniformly continuous over its domain $X \subseteq \mathbb{R}^n$ if:

$$\frac{|f(x_2) - f(x_1)|}{|x_2 - x_1|} \leq L \quad \forall x_1, x_2 \in X$$

(1)

Lipschitz’s condition measures the ratio of the distance between two points in the output space over the distance in the input space: the function fails the test unless the ratio of those distances is bounded for all points in the domain of the function.

A similar test can be applied to sets of training data obtained from human demonstration. Let us consider a relation defined by a set of input-output pairs

$$R = \{(x_i, y_i) : x_i \in X, y_i \in Y\}$$

(2)

and the relation is assumed to be in a function form:

$$y = f(x)$$

(3)

We can apply a Lipschitz-like condition by taking the ratio of the distance between two points in the output space over the distance separating them in the input space. If the ratio between any two points in the set $R$ is above some arbitrary threshold value, then the condition is not satisfied. This Lipschitz-like condition is a very useful tool in the context of skill transfer since it can determine if a relation defined by a representative set of points contains inconsistencies or discontinuities.

An experienced human always performs a task successfully and without hesitation. This suggests that the mapping from the human’s perception space to its control command space must also satisfy Lipschitz’s condition. If some pair of data points in the training set $R$ violates Lipschitz’s condition, this implies the input space $X$ for the training set $R$ does not completely characterize human perception of the process state.

Fig. 3 Geometric interpretation of inconsistencies due to missing input information

Namely, there are some critical process features missing from the vector of input variables $x$. This can easily happen when the input variable vector $x$ includes only direct sensors signals, e.g. force and position signals, while a human relies on some process information other than just force and position to make a control decision. This situation can be interpreted geometrically as shown in Fig. 3. The missing critical information lies along a dimension orthogonal to the original input space. Two points that are hardly separable in the input space (Fig. 3-(a)) may be far apart along the missing dimension (Fig. 3-(b)), which is how a human differentiates the two input points and thereby takes two distinct control actions. By introducing new dimensions to the input space, a set of properly selected additional variables could make the training data pairs satisfy Lipschitz’s condition. In [6, 17], Lipschitz’s condition was applied successfully to assembly and deburring tasks where consistent mappings were identified from human teaching data based on proper definition of perception spaces.

The Lipschitz test proved to be effective in examining the completeness of a given perception space. However, the use of the Lipschitz test is based on the assumption that human performance is consistent in terms of a certain target skill to be recovered from demonstration data. Physical data obtained from human demonstration inevitably could contain inconsistent information due to either measurement noise or human inconsistency. In [17], these inconsistent information was removed efficiently by using the Lipschitz test. In [5], Delson and West proposed an alternative method for interpreting human demonstration data. There the presence of human inconsistency in demonstration data was used advantageously to provide additional information regarding task requirements as well.
as strategies. One of the main features in Delson and West's work is that multiple demonstrations of the same task by the same person can be combined so that a more robust task strategy can be identified. This idea was demonstrated in [5] for an obstacle avoidance manipulation.

4. Prospect of Future Research

As discussed in the previous section, the identification of perception space is a critically important issue in human skill transfer. To teach human manipulative skills, it is necessary to know which pieces of information humans use and which particular aspect of the process they pay attention to. To represent a human skill, we need to identify a complete set of variables describing the information that the human perceives during the process. Based on the complete description of the perception space, the human skills and strategies can be represented properly and consistently.

This problem is a type of system structure identification, which is difficult to deal with. If the perception-action map describing a human skill is a linear map, the problem is rather simple; standard techniques based on identification error can be used to reconstruct the input space. Human skills, however, are highly nonlinear, hence traditional methods do not apply. The Lipschitz test described in this paper is a simple way of examining the completeness of a given perception space, and is applicable to nonlinear maps. The Lipschitz test, however, cannot be applied to noisy data or the ones containing inconsistent data. There is a way of alleviating the noise problem [8], but it is still an open question. Further investigation and the development of more powerful methods are needed to deal with inconsistent human data.

Studies on human skill teaching/transfer are not only useful for practical applications but also significant and essential for robotics research. Transferring human skills entails basic modeling and representation techniques, which are important issues in understanding manipulative strategies in general. Explicit representation and modeling of human behavior provide insights and manifest subconscious human skills and strategies. Moreover, direct observation and identification of human behavior, effective skills and novel strategies that have never been used in robotics can be discovered. Studies on human skill transfer may provide a new approach or a methodology for the study of manipulation and task strategies.

The issues central to human skill transfer are fundamental issues common to many other areas in robotics. In telerobotics and virtual reality, the communication of human intention and strategies as well as skills is a central issue. The broad field of human-machine systems and human motor psychology is directly related to human skill transfer as well. The utility of human skill transfer involves both practical applications and scientific importance, having significant connections to many related areas in robotics and beyond.

5. Conclusions

The key advantage of direct teaching by human demonstration is that the method is highly user-friendly; it requires no special knowledge of machine programming from the users, and it automatically extracts user intentions and strategies from task performance demonstrated by the users. From the teaching/playback approach for the early industrial robots, direct teaching has evolved into a class of highly sophisticated methods for transferring not just position intentions from humans, but also sensory-feedback, motion control laws as well as task-level strategy planning and adaptation laws. Several works have demonstrated the efficacy of direct teaching of human motion/force skills to robots. However, these implementations are still somewhat task-specific. In particular, in the attempt to recover a perception-action map from human teaching data, there are not yet systematic guidelines for constructing an adequate perception space that thoroughly captures essential task-level features that a human observes in his/her perception-action mapping process. One previous work using the Lipschitz test is good only for analysis of consistency for a given perception space. Further quantitative methods are needed to examine human teaching data, not only for constructing a meaningful perception space, but also for identifying inconsistency in human behavior and other possible noises inherent in teaching data. Previous results also revealed that inconsistent data obtained from human demonstration could in fact be used advantageously to extract additional task information for more robust and accurate robot motion. This is also a direction worth further pursuit.
References


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