# Tactile Sensors for a Programming by Demonstration System

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**Abstract**

*Easy programming methods following the Programming by Demonstration (PbD) paradigm were developed within the last years. The main goal of these systems is to allow the unexperienced human user to easily integrate motion and perception skills or complex problem solving strategies. Learning form human demonstration assume very vast sensory employment. Due to the fact that missing extracted information from demonstration mostly can be compensated by graphical, speech or gesture interaction, sensorial input simplifies the programming process. Describing unconsciously performed actions or motoric coordinations is very complex and in general not possible. This paper describes how tactile sensors are integrated in a PbD system which learns form human demonstration. Therefore a analysis of the used tactile sensor and its characteristics is performed. Further on the integration of tactile information in the systems cognitive functions is pointed out. Finally it can be concluded that the enhancement of a data glove with tactile sensors improves the analysis of human demonstration. Moreover, the supplied information increases the subsymbolic and symbolic task knowledge which leads to a more reliable recognition of the user's actions.*

## 1 Introduction

The development of service and personal robots — a upcoming area in robotics research— requires special programming interfaces. One of the major problems to be solved in order to successfully apply robots to service tasks is the problem of providing a proper programming and cooperation interface for unexperienced users. Therefore, learning systems are needed capable of extracting knowledge from watching users demonstration. Heterogeneous sensor inputs like vision, tactile or position information are required of such systems. Interactive programming interfaces are required that allow users to easily instruct a robot without having to follow a formal programming procedure.
A PbD system which serves there requirements has been developed during several years of our institute. Results of this work can be found in [6, 23, 5]. The integration of tactile sensors in the PbD system is the newest enhancement for the system's improvement. represent a further step for its upgrading. Our aim is not to transfer force-based assembly skills to robots by human demonstration. The motivation behind this work is to increase the reliability of our system by extracting more information that can be detected by vision or a data glove from human demonstration.

### 1.1 State of the Art

In recent years several robot programming systems were developed that follow the Programming by Demonstration (PbD) paradigm [2, 7, 14, 16, 19]. Most of these systems are focused on the task of reconstructing trajectories and manipulations a user demonstrates. Their goal is to reconstruct and replicate demonstrations or at least a set of environmental states with the highest accuracy possible. Other systems try to abstract from the user demonstration representing sub-goals that were important for a successful task solution. In [4] a classification of PbD systems like shown in figure 1.1 has been discussed. Therefore in the following only a brief overview is given. Referring to figure 1.1 on the *abstraction level* the learning goal can be divided in learning of *low-level or elementary skills*, mostly realized with neuronal networks [16, 2] and *high-level skills or complex task knowledge*[24, 11, 13]. Within robotic applications, *active, passive and implicit examples* can be provided for the learning process. Active examples indicate those demonstrations where the user performs the task by himself, while the system uses sensors like data-gloves, cameras and haptic devices for tracking the environment and/or the user interaction. Obviously, powerful

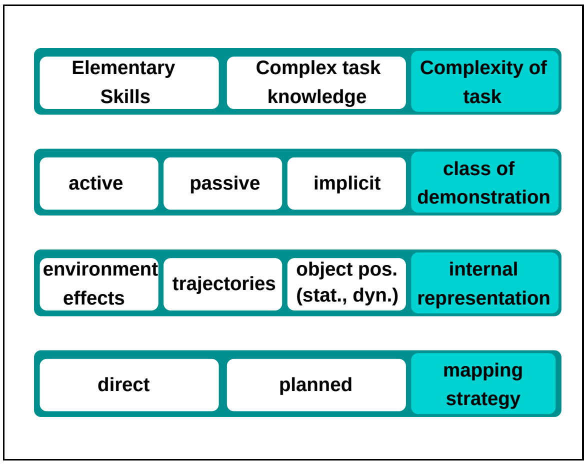


Figure 1: Classification features for PbD systems.

sensor systems are required to gather as much data as available [27, 15, 7, 26, 28, 14, 10, 19, 18, 30].

Most of these systems regard *effects in the environment, trajectories, operations and object positions*. While observing effects in the environment requires high level cognitive functions observing trajectories of the user's hand and fingers is a well understood task. Finally the representation of the user demonstration is been *mapped* on a target system. Therefore actions are *planned* based on the environment state and current goal or the observed trajectories can be *mapped directly* to robot trajectories using a fixed or learned transformation model [14, 12, 20]. The problem here is that the execution environment must be similar to the demonstration environment.

In the domain of recording tactile information many tactile sensors have been developed in the past ten and more years. Some good surveys of tactile sensing technologies were provided by Nicholls et all [22] and Howe [9]. Several researchers have used tactile feedback for determining object shapes or force primitives from users demonstration [1, 3, 17, 29]. Most of these works are trying to map the extracted force characteristics directly to robot actions [25, 8, 21].

## 2 PbD System for Manipulation Tasks

Within this section the cycle of our developed PbD system is briefly presented. An system overview is given in figure 2. It is theoretically capable of supporting each phase of the mapping process, but each component still needs improvement.

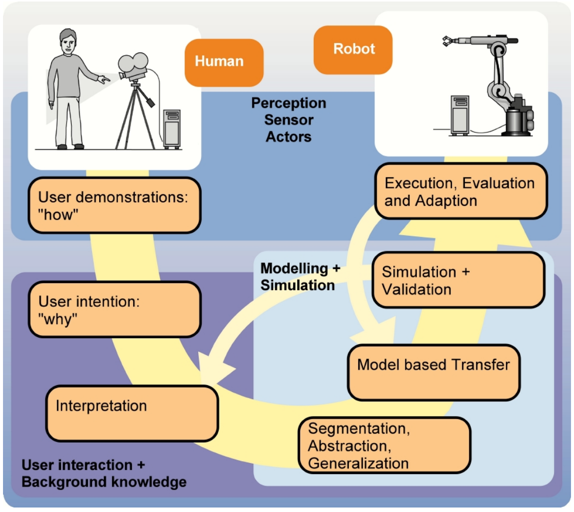


Figure 2: Overview of the mapping process between human and robot skills.

The PbD system consists of following basic components:

1. **Observation** For *PbD*, information about grasping states and objects is needed. Therefore, a combination of results of the processing of the finger angles given by a data-glove and of object classification done by an image processing approach has been realized. A VPL data glove and a Polhemus tracking sensor are used to record trajectories. The data-glove provides four angle values for each finger and the wrist, being sufficient to offer a good description of the actual posture of the human hand. Additionally, an active stereo camera head (3 grey-scale cameras, 2 turn and tilt modules) for fine tracking and a fixed ceiling color camera for rough tracking purposes are employed.

2. **Skill analysis** The starting point for skill analysis in manipulation tasks is the trajectory of the user's motions and his fingers' poses. In principle the presented method works on all trajectories, regardless whether they were recorded with a position sensor or whether they were derived from highly accurate vision or laser based sensor recordings. Beside the trajectory, a Data-base is needed, which contains sensor data, a set of action types, a set of elementary operations (EOs) and the world-model. The third major need of the analysis is the interaction between user and

system, which can be done via various interaction channels like text inputs, graphical interfaces or more intuitively via speech and gestures. This should reflect the intention of the user. During this phase the following steps are processed:

- *Trajectory segmentation* is done in order to divide the demonstration in meaningful phases that are associated with the different manipulations that the user has performed. For manipulation tasks the recognition of contact between hand and object is necessary in order to segment the trajectory.
- *Segment-wise trajectory analysis* The identified segments between contact operations are analyzed w.r.t. their local substructures.
- *Mapping the trajectory segments on EOs* The system generates hypotheses for EOs regarding the desired accuracy of the reconstruction.
- *Acquisition of the user's intention* Following the representation of the trajectory with the user intended accuracy, the object selection conditions are determined.

3. **Model based Mapping** At last the semantic information in form of human operations, and trajectories can be used for generating a real executable robot program. In our case a mapping strategy for every operator is available. The output of the model based mapping module is a sequence of elementary movements that are valid only for the chosen robot/gripper configuration and the respective environment. The sequence of movements is directly passed to the simulation module.

4. **Simulation and Validation** Simulation allows the validation of the action sequence previously built, performing the task in a virtual environment. A virtual model of the robotic system executes the task, interacting with virtual objects placed in the environment. One of the outputs of the simulation is a visual animation of the execution of the task. This allows us to check whether the task is executed correctly, according to the knowledge acquired. Simulation allows also performing some modification on the strategy implemented, or on the type of robotics system to use, so as to try several solutions and find out the most appropriate one(s).

5. **Execution** The validated sequence of elementary robot movements is then passed to the robot controller. Since the task execution has been previously validated in simulation, it is highly likely that the robotic execution does not fail, and that the system is able to adapt using force and position control.

# 3 Integration of Tactile Sensors in a Data Glove

One of the lacks of the above described PbD system is the accurate determination of grasp and ungrasp actions. To improve this tactile Sensors were attached on the fingertips of the data glove, as shown in Figure 4. The active surface of the sensors is covering the hole fingertips. The wires to the interface device are conducted on the upper side of the fingers, allowing the user to move his finger with maximal agility.

Figure 3: Tactile sensors on the fingertips of the Data Glove

## 3.1 Sensors Properties

For the experiments low-price, industrial sensors of the Interlink company, based on an Force Sensing Resistor (FSR) were used. This technology determines the behavior presented in the following. For our application an circular layout with one cm diameter of the active surface was selected. Applying a increasing force to the sensors active surface the resistance decreases. The FSR response approximately follows an inverse power-law characteristic ($U \approx 1/R$). For a force range of 1-100 N the sensor characteristics are

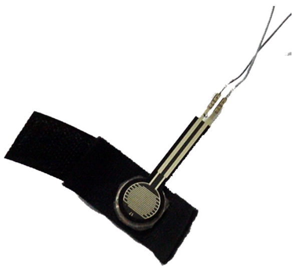

Figure 4: Tactile Sensor

good enough for detecting grasp actions. This range shows a hysteresis below 20% and the repeatability of measurements is around ±10%. Following these restrictions the force is quantized into $30 - 50N$ units.

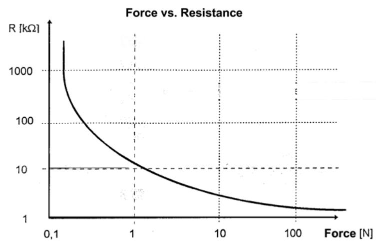


Figure 5: Force vs. Resistance

Some remarks for the use of the sensor have to be made. The active surface is very sensitive concerning bending ($r < 2.5mm$), since it can cause tenseness in the material. This may result in pre-loading and false readings. Therefore we applied the active surface on an thin and rigid plate. Proceeding so, good and reliable results are achieved. Whether this configuration shows little drift of readings when static forces are applied.

### 3.2 Signal Processing

For generating voltage from resistance difference a standard current-to-voltage converter is used. To achieve more accurate results a power stabilizer is integrated. A hardware low-pass filter is also included in the interface for smoothing the outputted signals. These are digitalized with an Avnatech PCL 818 Card. In our application a voltage range of $\pm 2.5V$ is digitalize with a accuracy of 12 Bit. The data is polled with a frequency of 25 Hz.
After smoothing the digital values with a software filter they need to be adjusted. For this purpose every sensor is calibrated individually. We assumed a linear characteristic so only the offset and scaling value has to be determinated.
$( \ CalVal = offset + scale * SensorOut \ )$

## 4 Integrating Force Results in the PbD Cycle

This section describes how the received force inputs are integrated in the PbD system. Thus integration in all involved phases mentioned in section 2 will be described in detail.

- *Observation* In this phase the physical integration of the tactile sensors is done in order to improve the observation process. The sensor data base and the world-model had to be expanded for including force inputs. This is important because the adequate internal representation is significant for the following process of sensor fusion, analysis or feature extraction.

- *Trajectory segmentation* For manipulation tasks the recognition of contact between hand and object, is to be performed in order to segment the trajectory. Evidently this is easily obtained from the force values with a threshold based algorithm. To improve the reliability of the system the results of both the new and the old recognition routines (based on finger poses and velocity and acceleration trajectories analyzed w.r.t. to minima) are merged.

- *Mapping the trajectory segments to EOs* So far the grasp classification is made by a hierarchical neuronal network. The input are joint angles provided by the data glove. In spite of the good result of this classificator [6], a controlling algorithm based on contact information can lead to further improvements. Thinkable is generating a set of sorted grasp hypothesis and a selection method based on force information.

- *Model based mapping* As mentioned, the sensors show a drift on statical strain. Therefore, the gained information is rather qualitative than quantitative. Due to this fact ten classes can be defined for characterizing the grasping force. This can be used to determine the right grasp type to map to. So, the grasp type is defined by the contact points and the applied force.

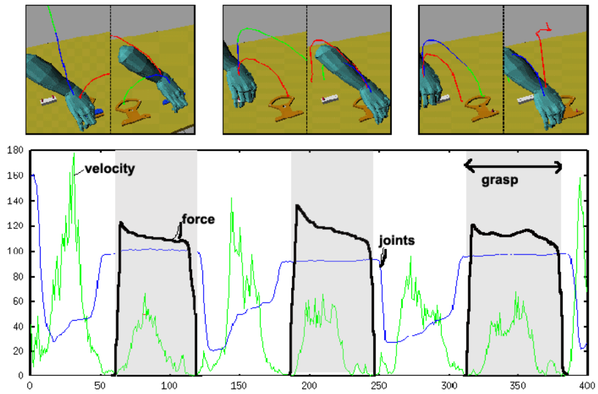


Figure 6: Processing three grasp-ungrasp actions

## 5 Conclusion and future enhancements

In course of this article we pointed out the motivation of integrating tactile sensors in our PbD system. Further the characteristics of the used sensors and attachment to data glove was explained. Finally we showed how the phases of the PbD cycle benefits from the achieved force information. In conclusion it can be summarized that, by integrating tactile sensors in the system we made a further step to improve our PbD system, w.r.t. its cognitive abilities.
Future works will analyze force characteristics with respect to grasp type, weight, surface features of the grasped object and trajectory type in order to extract further significant information. This will be integrated in the systems knowledge base and used for task recognition or mapping the demonstrated actions to a robot system.

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