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# Semi-Autonomous 3$^{\text{rd}}$-Hand Robot

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http://3rdhandrobot.eu/

## Abstract

*We present the principles, current work and plans for the EU-FP7 Project* Semi Autonomous 3$^{\text{rd}}$-Hand Robot. *In this project, we pursue a breakthrough in flexible manufacturing by developing a symbiotic robot assistant that acts as a third hand of a human worker. It will be straightforward to instruct even by untrained workers and allow for efficient knowledge transfer between tasks. We demonstrate its efficiency in the collaborative assembly of furniture.*

## Approach

Current robots in real-world industrial applications are either preprogrammed or teleoperated, with only few exceptions, lacking any autonomy at all. At the other extreme, the field of artificial intelligence has so far been unable to endow robots with full autonomy, and the prospect of fully-autonomous robots is uncertain at best. We challenge the current thinking in industry and academia on both the future of robotics and artificial intelligence as well as on the nature of the long-awaited robotic killer application by suggesting that a promising alternative, achievable in the foreseeable future, lies between these extremes.

The alternative we propose is *semi-autonomous human-robot collaboration*. This new robotics paradigm is likely to result in a class of robotic systems that are *proactive*, can be *programmed and commanded by instruction*, are capable of *skill self-assessment*, and have an *explicit model of team behavior*. These principles will allow a revolution in the way humans and robots work together by changing the usual way we program and interact with robots:

**Instruction replaces Programming.** Under frequent occurrences of new situations, it is not possible to program each new task with abstract programming languages. Instead, intuitive programing methods must be devised. Our instruction framework generalizes *learning from demonstration*, *active learning*, *mutual adaptation*, and *human guidance* to allow a laypeople to command a robot to work on collaborative tasks.

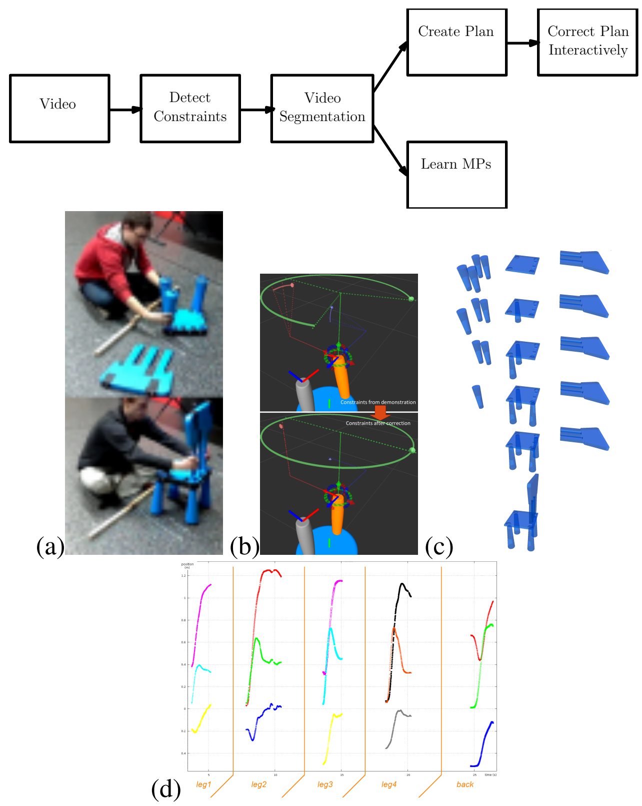


Figure 1. Interactive Learning Framework for extracting a high-level task representation as well as reusable motor primitives from a user demonstration. (a) Task Demonstration; (b) Interactive correction of the acquired knowledge using a GUI; (c) Automatically detected key-frames of the demonstration; (d) Motor primitives extracted from the demonstration.

**Knowledge Transfer enables Fast Task Switching.** Although new tasks will continually require new skills of the robots, most will exhibit significant similarities. If such invariant properties are exploited, we can substantially improve the efficiency of task switching – significantly beyond what either instruction alone or standard generalization properties of the learning algorithms can achieve. Hence, we must devise methods that at any state *know what they know* as well as what knowledge needs to be acquired.

**Semi-Autonomy replaces Teleoperation or Full Autonomy.** Many products require a level of dexterity and precision that benefits greatly from *collaboration between people and robots*. Here it is essential that the robot is able to ask for help when its skills are not sufficient. Also, for fluid interaction it will need to *interpret the users' needs and anticipate their requests*, either to act according to the operators' intentions or to *avoid unsafe situations*.

### Expected Results

Semi-autonomous robots go beyond *teleoperated robots* in that they are trained to do their jobs without step-by-step guidance. Instead of requiring an operator, these robots operate proactively and blend their operation with that of their human coworkers. The key idea is the *combination of the precision, force and speed of robots with the dexterity, reasoning and intelligence of humans*. Rather than operating independently, the robot becomes a *semi-autonomous* part of a mixed human/robot assembly team, within which it incrementally learns to fulfill its role based on intuitive human *instruction*. We introduce instruction as the combination of *demonstrations* (both correct behavior and counterexamples), *guidance*, *self-adaptation*, and *active querying* in an interactive process. Human and robotic coworkers can *switch roles*, and the robot can *predict and adapt to the human co-worker* both at a low control level and at the higher level of *understanding preferences and limitations of its collaborator*.

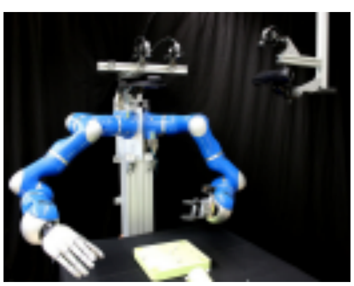

Figure 2. The experimental platform setup consisting of two KUKA lightweight arms, two DLR-HIT five-fingered hands, two Kinect cameras, four CMOS sensor cameras, and a motion capture system (the latter not visible in the picture).

## Work progress

In the following we summarize the current status one year into the project. A high-level overview of our interactive learning framework is presented in Figure 1 and in a a video. It considers all factors that need to be taken into account to learn a complete description of a task in an intuitive way efficient enough to reduce the programming effort and to reuse learned skills. We are developing software tools that allow easy programming and interaction with a robot and simultaneously address the learning, programming and execution problems. As we rely on learning methods, special care is taken to ensure that such software tools are able to provide the user information about learning progress and uncertainty of the robot and its state during task execution.

**Perception** We developed a probabilistic, appearance-based pose estimation (PAPE) method that integrates diverse feature types including edge orientations, depth and color. This method is useful for realistic grasping / manipulation tasks involving textureless objects and imprecise models. To estimate gaze and gather cues for human-robot interaction, we implemented a face tracking system using Regularized Landmark Mean-Shift (RLMS) [7] in combination with POSIT [3] for head pose estimation. Based on head pose and fiducial points extracted by the face tracker, we obtain a refined estimate of gaze. Together with hand pose estimation and gesture recognition they will aid in human-robot interaction.

**Motor Primitives** We address multiple challenges in the acquisition of motor primitives and their application in coordinated work. First, we plan robot motion in a way that obeys high-level constraints learned from human demonstration (see videos of assembling a toolbox and a chair). Secondly we consider how to generalize and execute motor primitives in coordination with a human partner. We studied how to learn and validate *interaction primitives* for handover of different parts during assembly tasks [5], to address multiple interaction patters between the human coworker and the robot assistant [4] using unlabeled data (see a video). We developed new ways to generalize probabilistic primitives during grasping using warping functions [2].

**Segmentation of Trajectories of Multiple Objects** An assembly task can be interpreted as a sequence of manipulations acts that change the constraints between pairs of objects. We created several methods that build upon this notion, one based on a generic CRF model that models a conditional probability distribution between the motions and postures of different objects [1], and a complementary method where the segments result from clustering motor primitives rather than relations between objects.

**Acquiring High-Level Task Plans** An assembly task is a complex skill that includes both high-level planning and low-level action execution. The high-level plans generalize better among different objects and situations and are easier to interpret by humans. To learn such plans we introduced a new inverse reinforcement learning method that works in the relational domain [6] (see a video illustrating transfer of learned plans between objects).

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