Technologies for the Fast Set-Up of Automated Assembly Processes

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RESEARCH PROJECT

Technologies for the Fast Set-Up of Automated Assembly Processes

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Abstract In this article, we describe technologies facilitating the set-up of automated assembly solutions which have been developed in the context of the IntellAct project (2011–2014). Tedious procedures are currently still required to establish such robot solutions. This hinders especially the automation of so called few-of-a-kind production. Therefore, most production of this kind is done manually and thus often performed in low-wage countries. In the IntellAct project, we have developed a set of methods which facilitate the set-up of a complex automatic assembly process, and here we present our work on tele-operation, dexterous grasping, pose estimation and learning of control strategies. The prototype developed in IntellAct is at a TRL4 (corresponding to 'demonstration in lab environment').

Keywords Robotics · Automated assembly · Pose estimation · Robot control

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1 Introduction

In the IntellAct project [IntellAct (2011–2014): Intelligent observation and execution of Actions and manipulations, http://intellact.sdu.dk/], we created new technologies for facilitating the setting up of automated assembly processes with robots. The use of robots is still considerably hindered by the complexities involved in setting up robot solutions since these usually require expert knowledge and also significant time for testing and fine-tuning. The developed technologies in IntellAct allow for faster set-up times, which is crucial for the use of robots especially for

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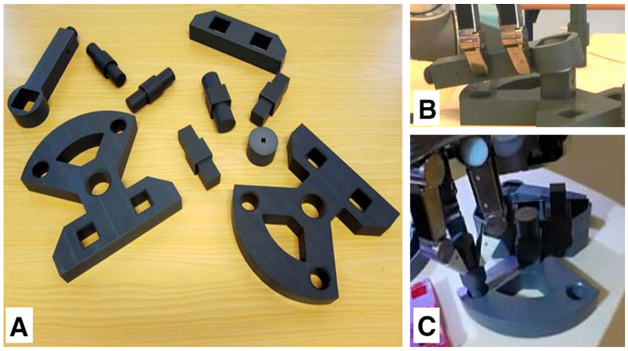

Fig. 1 **a** Cranfield assembly task. **b** An insertion action from the Cranfield benchmark. **c** An peg-in-hole action from the Cranfield benchmark

small batch size production (also called 'few-of-a-kind production').

In the IntellAct project, we used a well known assembly task—the so called Cranfield benchmark [1] (see Fig. 1a)—as a test case. The Cranfield benchmark reflects problems also prevalent in other assembly tasks typically occurring in companies, both in terms of complexity of the individual assembly actions as well as the number of entities to be assembled. It involves 5 Peg-in-Hole (PiH) operations (see Fig. 1c) as well as other (reverse) insertion tasks (see Fig. 1b) with objects of rather different size and shape. However, as it will become clear from this article, the technologies developed in IntellAct are not restricted to the Cranfield benchmark but are generically applicable for a wide class of assembly tasks.

Set-up times for automated assembly solutions are dominated by a number of sub-problems: First, often specialized grippers are used for grasping and manipulation that allow for good force control (see Fig. 2a). These grippers often need to be designed or refined for particular objects occurring in the assembly process. Moreover, the different shapes and sizes in the Cranfield set do not allow for the use of only a single simple gripper type. Second, in today's robot solutions it is often required to assure that the position and orientation of objects is predetermined with a high degree of precision. This usually requires specific machinery for precise positioning, as shown in Fig. 2b. This causes additional hardware costs but usually also requires some expert knowledge at the end-user side to integrate such systems in the automated assembly system. Third, robot grasps and trajectories (including appropriate forces) need to be taught in or programmed, which in general is done through menu-oriented control devices (see Fig. 2c) or kinesthetic guidance, both potentially quite tedious procedures.

However, new technologies have been developed over the last decade that address the above mentioned problems. Firstly, dexterous grippers—which are becoming increasingly relevant for industry—facilitate the realization of a variety of grasp types and by that are able to deal with objects of rather different size and shape (see Fig. 3). Secondly, vision-based pose estimation is entering assembly processes and relieve the need for designing systems that require high accuracy of object positions. Thirdly, new methods and devices for teaching trajectories to robots are emerging. Fourthly, control strategies have been developed that can adapt to new task contexts. In the course of the IntellAct project, it became increasingly clear that the first two points and the fourth point are tightly connected, since the use of dexterous hands as well as pose estimation by vision introduce uncertainties in the process that control strategies need to be able to compensate for.

2 Robot Platform

Our robot platform MARVIN is a robotic platform designed to simulate industrial assembly tasks (see Fig. 4a). The setup includes both perception and manipulation devices. The perception part includes three sets of vision sensors, each set consisting of a Bumblebee2[1] stereo camera, a Kinect sensor as well as a projector which is used to project texture on the objects in case the Bumblebee cameras are used (Fig. 4c). In general the precision of 3D reconstruction was higher with the Bumblebee cameras than with the kinect cameras; however the achievable frame-rate was higher with the Kinect cameras. The three vision sensor sets are placed with approx. 120° separation, as shown in Fig. 4b. In addition to the cameras, the platform is also equipped with high-precision magnetic trackers of the type trakSTAR[2] providing 6D poses simultaneously from up to four sensors. For manipulation, two Universal Robots (UR) are mounted on each side of

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1 http://www.ptgrey.com/products/bumblebee2.

2 http://www.ascension-tech.com/realtime/RTtrakSTAR.php.

Fig. 2 **a** Specialized gripper for a specific assembly task with a specific object. **b** Typical feeding machine used in automated assembly. **c** Control panel based programming of the UR robot arm

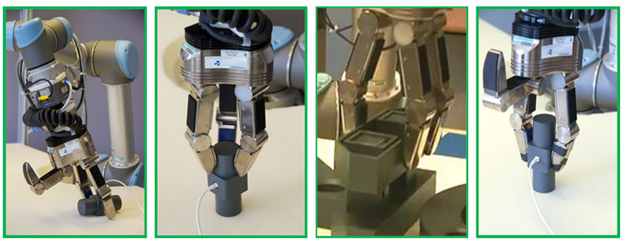

Fig. 3 Dexterous grasping of parts of the Cranfield benchmark

the main table (see Fig. 4a). One robot is equipped with a Schunk SDH II gripper. Although the Cranfield objects vary significantly in size and shape, the SDH-II hand is able to grasp all objects of the Cranfield set (see Fig. 3). On one UR-arm, a force-torque sensor is mounted between the robot end effector and the SDH gripper. Force/torque information is crucial for the learning of execution actions as described in Sect. 3.3. For further details see [2].

3 IntellAct Technologies

The grasps are taught in by means of tele-operation (see Sect. 3.1). The need for exact object positioning is overcome by vision-based pose estimation using a multi-camera set-up (see Sect. 3.2). Finally, robot control strategies based on Dynamic Motor Primitives (DMPs) [3] are established, which allow for the adaptation of the taught-in trajectories to the robot embodiment and to the concrete task context (as described in Sect. 3.3).

3.1 Teleoperation

Tele-operating control methods should be rather intuitive and should also allow the user to ‘act naturally’, and by that facilitate the transfer of human manipulation experience and intelligence into the tele-operated process. Assembly actions can be broken down into three subphases: The first phase concerns the grasping of objects, the second concerns the transport of the object to a position in which then, in the third phase, the physical interaction between two objects—the actual assembly operation—occurs.

Within the IntellAct project, we have experimented with a variety of tele-operation methods, using different control modalities, such as a data glove (see Fig. 5a, c) and a control peg from the Cranfield set (see Fig. 5d). In both data glove and control peg, a trakStar sensor was integrated, which tracks the 6D pose relative to the transmitter and transforms this to the robot on a 1:1 scale (see [4] and Fig. 5b, d). In addition, we also investigated the use of the Universal Robot control panel and kinesthetic guidance. The aim was to determine what the advantages and disadvantages of each tele-operation modality are with respect to success rate, efficiency and number of errors. Our results show that the data glove (see [5]) yields relatively low success rates since human embodiment can interfere with intuitive use [4].[3]

The control peg was found to be superior also with respect to truing time needed and intuitive handling. Similarly, while users prefer the control panel because it seems highly transparent and while it is very well suited for large movements of the robot, fine-tuning the gripper on an object turned out to be more complicated than expected using the control panel [6]. Furthermore, our experiments show that in the tele-operation modality, errors occur concerning too much pressure, self-collision and singularity (which means to bring the robot into a position that does not allow to read out inverse kinematics for learning from demonstration). Interestingly, users have no intuitions about how to avoid or even resolve such errors [7]. Moreover, the errors are not due to the tele-operation speed [8]. In sum, our experiments have shown that the choice of teleoperation modality can have a considerable impact on the data quality for learning by demonstration.

[3] The experiments in [4, 6–8] were done by people not knowing the system before.

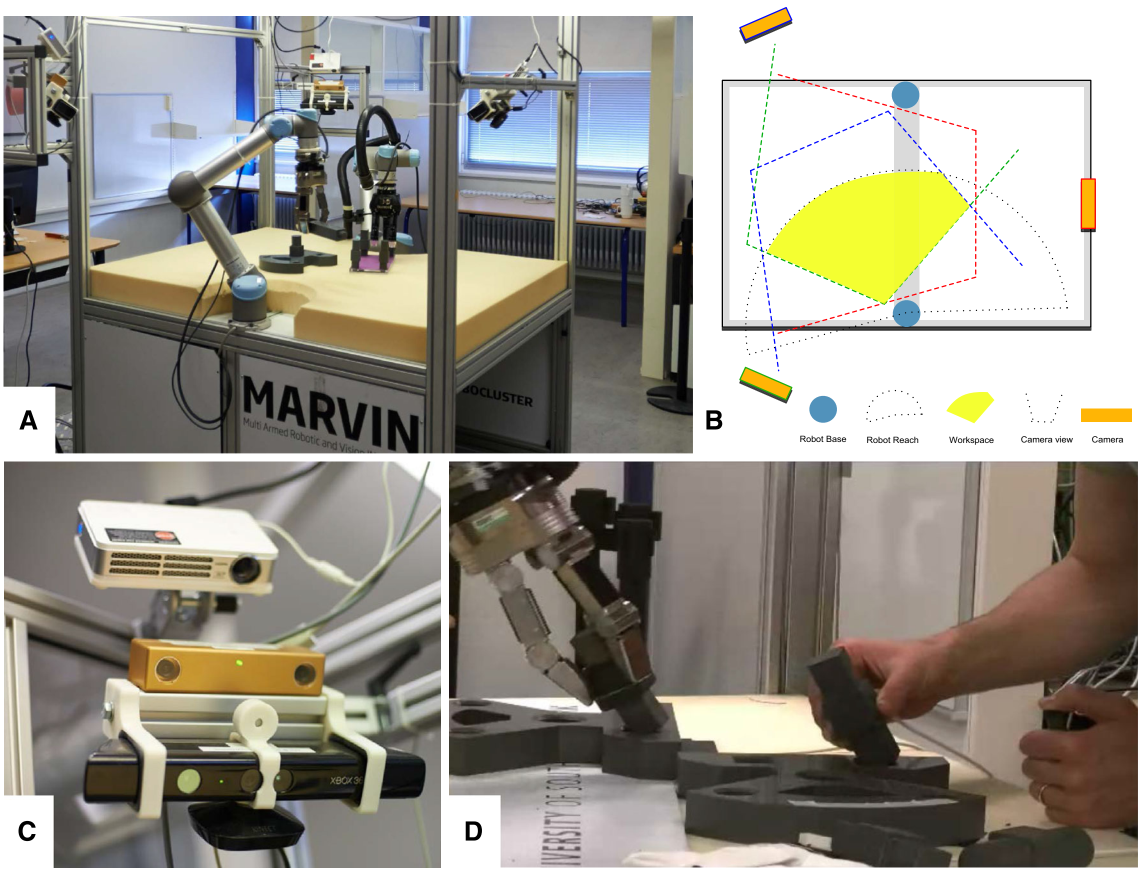

Fig. 4 **a** MARVIN platform. **b** Top-view indicating the workspace of the two robots and the viewing field of the three distributed camera systems. **c** The two vision sensors and projector. **d** Tele-operation and recording of forces and torques

In the IntellAct project, we have eventually used the data glove mode for teaching the first phase discussed above (i.e., grasping). For the second phase—i.e., reaching a position in which the third assembly phase in which physical object interaction occurs can start—no demonstration was required since appropriate trajectories can be directly computed from the object poses extracted from vision and the target poses. A direct use of the objects (as shown in Fig. 4d in the context of peg-in-hole actions) was then used to teach in the final assembly phase to allow for an optimal transfer of human dexterous skills. In particular, forces and torques similar to the forces and torques that were experienced by the human could be recorded by the FT-sensor in the wrist of the robot in such a set-up. This information was then used for the learning of appropriate motor control strategies as described in Sect. 3.3.

The second demonstration[4] at the final review shows the teaching of the action by means of the technology developed in IntellAct.

[4] See http://www.youtube.com/watch?v=c4Yc3_ES2YY.

3.2 Pose Estimation and Tracking

A particularly challenging problem is the perception and monitoring aspect. Especially in few-of-a-kind production environments, there is a need to be able to adapt to novel objects, which can be recognized and localized with high reliability and precision. This challenge is fundamental to computer vision, and a great body of work is dedicated to a generic detection from both, 2D (see e.g., [10]) and 3D (see e.g., [11]) data. An additional complication arises under assembly tasks, since the vision system has to be able to track relevant parts, potentially undergoing complex manipulations with the risk of occlusions.

For the MARVIN platform we have developed an array of algorithms to deal with these perception problems. Our object recognition system performs all processing on 3D point clouds, and for this reason no complicated training phase is required, assuming that a 3D CAD model is available. This allows us to describe objects and their locations in the coordinate frame of the acting robot using the calibrated robot-camera extrinsics. During processing, 3D data from the scene is captured by both 2.5D sensors

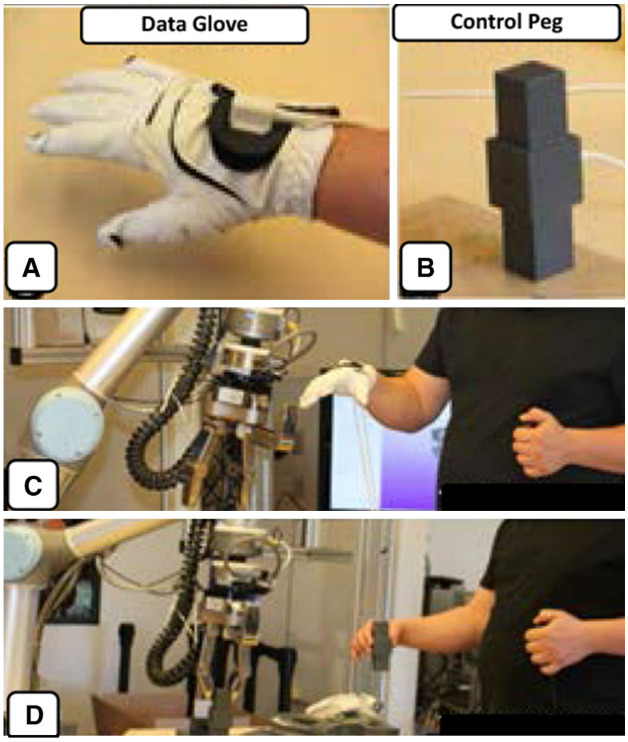

Fig. 5 Two tele-operating modes utilizing the trakStar sensor: **a**, **c**: Teleoperation via the data glove. **b**, **d**: Teleoperation via the external device

(Kinects) and stereo cameras (see also Fig. 4c). The objects involved in the process are in our case given as CAD files which we have sampled to point clouds, but our platform also allows for capturing novel objects from multi-view stereo or Kinect to obtain an object representation. We outline the proposed algorithms for recognition, pose estimation and tracking below. An evaluation of the monitoring system with focus on the tracking is presented in [12].

3.2.1 Object Recognition

At the very beginning of a process, the perception system is presented with a scene occupied by an unknown number of objects. To recognize which objects are present, we use the algorithm presented in [13], which is based on multi-view Kinect observations to cover the viewing sphere. The objects in the scene are described by global histograms capturing both appearance and geometry statistics. Each object histogram is fed to a random forest classifier [14], which has been pre-trained for the known objects.

3.2.2 Pose Estimation

Upon completion, the object recognition system returns the identities of the parts present in the scene. We now apply an efficient pose estimation algorithm proposed in [15] for obtaining the absolute orientation and translation of all the objects. This algorithm implements a prerejection step based on low-level 3D geometric invariants on top of the RANSAC [16] algorithm for a fast search for the correct pose. This leads to a running time of less than 0.5 s per object. The output of the recognition and pose estimation systems for the Cranfield set is shown in Fig. 6, left, with the aligned object models indicated by random colors.

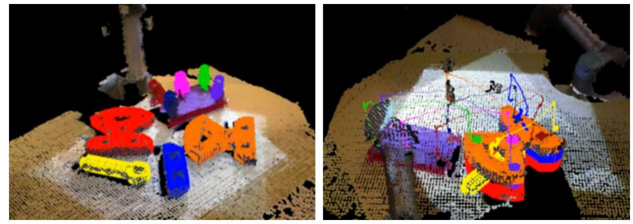

Fig. 6 *Left* recognized Cranfield objects and their estimated poses, shown by random colors. *Right* state of the tracking system, seen from a different camera view, upon completion of a complex assembly sequence performed by the robots. Each object is correctly monitored during the sequence, shown by *colored tracks*

3.2.3 Tracking

When all object identities and their locations have been recovered, a trigger is sent to initiate the manipulation system and from this point on the objects can move in an unpredicted manner. To maintain the objects in moving sequences, we apply a particle filter based tracker [17]. This tracker directly makes use of the 3D model representation, and provides a reliable monitoring of the objects during various manipulations. Using CPU parallelization, the algorithm runs in real-time, which is crucial for online monitoring. A visualization of the end configurations and the foregoing tracks of the Cranfield objects can be seen in Fig. 6, right. The performance of the IntellAct vision system can also be seen in a video[5].

3.3 DMP Learning

One of the major requirements for a faster set-up of automated assembly systems is robustness and fast adaptation to some unexpected environment changes. There are many aspects that can affect the final success of an assembly operation, such as non-precise pose estimation of objects, uncertainties about the gripping pose, small tolerances in object shape, etc. Assembly processes are characterized by the fact that very large forces can arise from small tolerances in object poses and shapes, which can result in failure of the operation or even in damage to the robot and the equipment. It is therefore necessary to provide

[5] See https://www.youtube.com/watch?v=LXhzSckFy9I.

methodologies that enable on-line adaptation of assembly policies in presence of uncertainties. Some previously proposed solutions rely on passive mechanical devices mounted at the robot wrist, such as Remote-Center-of-Compliance. In our work, we focused on adaptation based on explicit force sensing and corresponding robot actions, which we refer to as active strategies. Such strategies can account for larger positioning errors and can therefore be used for more complex assembly operations [19]. In the past, many active force control approaches were proposed to solve Peg-in-hole tasks with robot manipulators [20, 21]. One problem that often arises in these approaches is that the optimal control policy depends on the shape of the peg and the hole. The adaptation of control strategies to the shape of the manipulated objects is therefore often defined manually by a skilled engineer [22]. Despite this, the assembly speed achieved by active approaches is still not comparable to humans, since force control strategies usually require low speed in order to assure stable operation in presence of environment uncertainties [19]. When high gain force control was used in our experiments, the peg often got stuck in the hole and couldn't be inserted in its entirety. This gave rise to the key idea underlying our approach, namely to first execute the movement slowly and then to increase the speed of execution gradually based on the prediction of force feedback through the adaptation provided by an appropriate learning algorithm. Since humans are very good at performing assembly tasks that require compliance and force control, we use human demonstration of the task as a starting point. Our approach is to associate pre-recorded Cartesian space trajectories with force profiles sensed by the robot hand, which arise due to contacts between objects involved in an assembly operation.

Since our trajectories are specified in Cartesian space, we can transform them to new workpiece configurations, which can for example be recorded by vision. However, PiH-like tasks normally fail if the recorded and transformed trajectories are just repeated without any feedback control. Even small noise, which is always present if the workpiece pose is estimated by vision, can introduce large discrepancies between the recorded and current force profiles. In our approach we thus slow down the execution and adapt the recorded and transformed trajectories to better match the force profile associated to the recorded trajectory with the force profile of the current trajectory.

In order to implement our approach, which allows continuous temporal and spatial modification of the initially demonstrated policy, we applied the framework of Dynamic Motion Primitives (DMP), initially proposed by Ijspeert et al. [3]. A DMP contains free parameters that can be computed from a single human demonstration to encode the demonstrated trajectory. In contrast to most trajectory representations, which are time dependent, DMPs are phase dependent and only indirectly dependent on time. Through a simple modulation of the phase, we can change the time evolution of the encoded movement, which enables to implement our first idea: to slow down the assembly task execution whenever excessive forces arise. This gives the robot enough time to adapt to the previously recorded force profile through the application of iterative learning control [23, 24], which results in a stable execution of PiH-like tasks in new configurations. More details about the DMP modulation approach can be found in [18].

Especially in industry, there are a lot of operations that need to be executed many times in exactly the same configuration. Even in natural environments, tasks often need

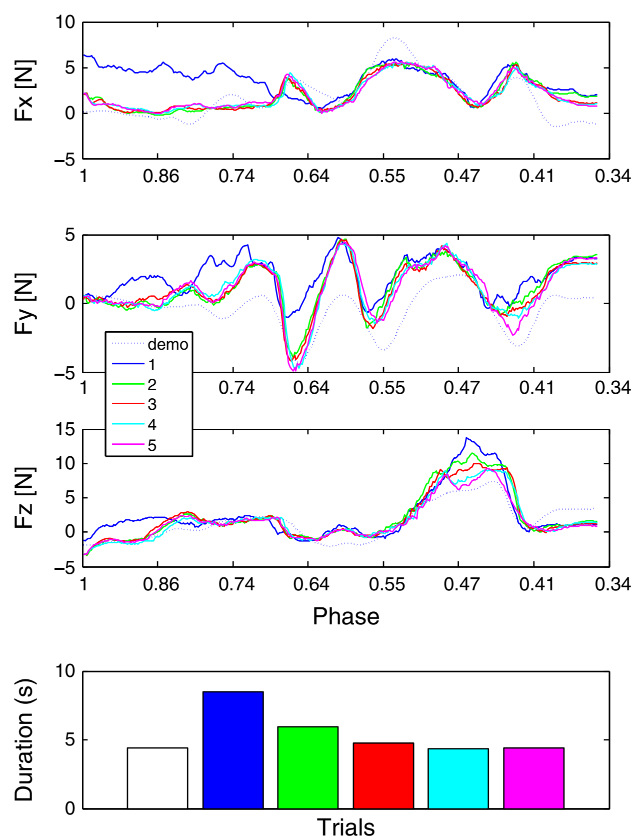

Fig. 7 The *upper three graphs* show the sensed forces as the function of phase. The *dashed trajectory* shows the forces recorded during training as the function of phase. When the task needs to be executed in a new workcell configuration, the developed DMP playback algorithm with phase modulation and feedback control enables the robot to successfully execute the task in the first attempt (denoted here by 1), albeit with the increased execution time. Using phase modulation procedure described in [18], the execution is slowed down if the sensed forces deviate from the forces recorded during human demonstration. This process enables the robot to adapt its movement so that the sensed forces become closer to the recorded forces. In subsequent repetitions of the task, there is less need for phase modulation and the execution time can be reduced by a factor of more than 2. Most of the improvement occurs in the first two adaptation steps

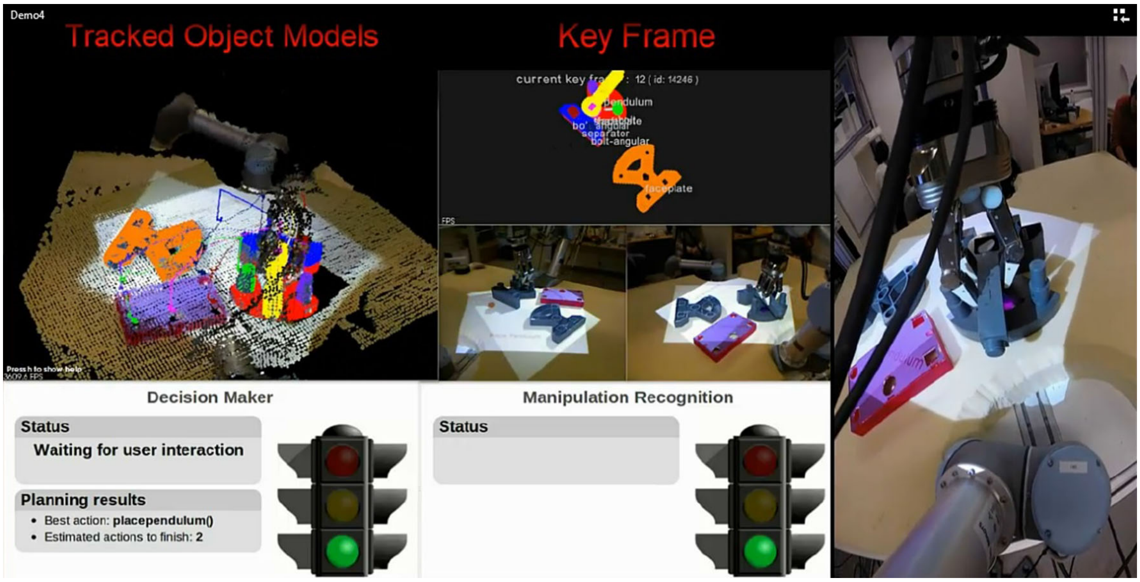

Fig. 8 Cranfield assembly at the second last assembly step. *Top left* the tracking history of different objects and the currentstate of the vision system in IntellAct. *Top middle* estimated poses and images taken of two of the kinect cameras. *Right*view from a camera installed on the robot arm. *Bottom left* output of high level planning modules not described in this paper

to be repeated many times. Humans can improve their skill knowledge by repeating the same action over and over again. The same approach is adopted by our system, where the information about the force profile tracking error is exploited to improve the performance in the next repetition of the same action. This is accomplished through a DMP adaptation procedure described in [25]. In our experiments we showed the improvement of execution in terms of reduction of execution time and force tracking error. On the average, after executing the desired operation 5 times, execution time could be decreased by a factor of more than 2. The forces could also be reduced and made more similar to the ones recorded during human demonstration. The learning of control strategies is shown in a video[6]. Quantitative results are shown in Fig. 7.

4 The IntellAct System

A video[7] shows the complete assembly of the Cranfield set (except the screwing action), which has also been demonstrated live at the review. All actions have been taught-in by human demonstration as described in Sect. 3.1, pose estimation and tracking are performed as described in Sect. 3.2 and the control of the executions in the third phase of execution when object-object contacts occur is performed as described in Sect. 3.3. Note that one screwing action (the screwing of a cylinder onto the pendulum) has not been implemented on the MARVIN platform due to the difficult to control compliance of the Universal Robot arm. This screwing however, has been implemented by one of the partners on a KUKA lightweight arm.

The system is able to monitor a complex scene with nine objects in terms of pose estimation and tracking (Fig. 8 shows a screenshot of the display of the IntellAct system). Initial object recognition for the rather small pegs—which were basically indistinguishable even for humans in the generated 3D point clouds—was done in a larger magazine in which the pegs were stored. However, pose estimation and tracking were done on the full nine objects independently using two kinect cameras in parallel. The robot could move with normal speed in that process. The complete assembly takes approximately 9 min, which is still much more what a human would require which would be less than a minute. The complete assembly succeeded in ca. 50 % of the trials. For most errors rather minor technical modifications could have prevented the errors occurring (e.g., workspace constraints).

Note also that the system is able to recover and learn from mistakes. This has been shown in another demonstration at the final review[8]. In this demonstration, a peg is taken out of the gripper of the robot by an interfering human and is then put on the table in an unknown pose (a laying pose instead of the usual upright pose). The robot realizes that it is not able to deal with the novel situation and requests then input from a teacher to deal with it. After demonstration, the robot than extends its repertoire of

[6] See http://www.youtube.com/watch?v=c4Yc3_ES2YY.

[7] See http://www.youtube.com/watch?v=LXhzSckFy9I.

[8] See http://www.youtube.com/watch?v=zW_zH80IO_M.

actions an dis able to deal with a similar situation in the future.

5 Conclusion

In this article, we have described technologies which are relevant for the fast-set up of robot solutions. Decreasing set-up times and complexity involved in establishing robot solutions is crucial for an economical use of robots especially for few-of-a-kind production. This is also crucial for maintaining and increasing production in developed countries. In the last decade, new technical developments have occurred with the emergence of new dexterous grippers, easy to program robots, cheap 3D sensors and increasingly robust vision algorithms and advanced control strategies. In IntellAct we showed that when vision and dexterous grasping are applied, the robot control strategies need to be robust to pose uncertainties. Transferring human manipulation skills to robots is therefore crucial as well as an autonomous adaptation of the control strategy to the actual robot set-up.

In IntellAct, we covered all aspects required to establish systems in an industrial context that can be set up faster than it is the case today. The IntellAct system is a prototype at Technical Readiness Level[9] (TRL) 4. The next step is—now in interaction with companies—to increase the TRL level further such that the technology developed in IntellAct has an impact on the use of robots in production. For that, a number of rather engineering issues need to be addresses such as efficient workspace management, increasing user friendliness as well as the intuitiveness of different aspects of the system. While speed concerning vision only needs to be increased by a minor factor, calibration routines still need to be more easy to use.

The use of dexterous hands in IntellAct gave promising results. However, how such devices perform when they are used over several days still needs to be shown. An alternative to using dexterous grippers for avoiding a tedious design process of specialized grippers could also be the learning of specialized finger shapes in simulation as done in [26].

Finally, execution speed in the third phase of an action—when physical contact between objects and high forces occur—is still rather slow. We are currently working on achieving even higher execution speeds than in the human demonstration by speeding up the recorded trajectories via reinforcement learning and iterative learning control [27]. However, all of these issues do not pose big scientific but rather engineering challenges and what is now required is the possibly painstaking process of starting from a prototype and arriving at a user friendly system that works reliably in an industrial setting, or in other words, advancing the system from TRL 4 to TRL 6 (i.e., from 'Integrated basic technological components' to 'testing prototype in a relevant environment').

[9] The Technical Readiness Level indicates the maturity of evolving technologies. It ranges from TRL 1 (basic technology research) to TRL 9 (system operating successfully under normal working conditions).

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