Visual servo guided cyber-physical robotic assembly cell

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Abstract: Advanced robotic assembly systems are promising great benefits to the manufacturing sector, once the shortcomings of the current technologies are overcome. One of the biggest obstacles to introducing flexible robotic systems is the ability of robots to sense and perceive the semi-structured or unstructured environment. This paper presents a cyber-physical system based framework of a robotic assembly cell that is capable of recognizing resources of assembly processes, based on information from various visual sensors and updating and adapting the assembly plan in the digital twin of the robotic cell. Thus, calculates and executes feasible motion plans of the robots based on accurate digital information. The application of the framework is demonstrated in a physical assembly process.

Keywords: Process Planning, Intelligent Manufacturing Systems, Intelligent Robot Services in Manufacturing

1. INTRODUCTION

A recent study on advanced robotic systems (Link et al., 2016) concludes that the promising economic impact of the next generation advanced robots can only be achieved if the flexibility of these systems is substantially increased. There is a great contrast with current-generation industrial robots that work in highly controlled environments isolated from workers out of safety concerns, using laborious teach-in based robot programming methods. Assembly systems of customized and economic production call for a new level of flexibility, reconfigurability, reusability, and changeability on the shop floor (Krüger et al., 2017).

The lack of adaptability of robotic assembly cells is commonly rooted in the inaccurate knowledge of the positions of parts and resources within the work cell. This imprecision implies that certain assembly operations are persistently assigned to human operators, who are capable of planning and executing fine movements based on their own perception. There is a growing trend in the research literature to introduce some kind of feedback control mechanism—similar to human perception system—to robotic cells as a means to improve their flexibility and reconfigurability (Hu et al., 2011; Leu et al., 2013)

Maropoulos et al. (2008) discuss the need of a metrology-enabled assembly automation especially in case of large-scale applications such as aerospace assembly. Traditionally the industrial perception of metrology being simply a verification stage that follows production and assembly, rather than being an active element of the manufacturing sequence.

Numerous researchers reported solutions that increase the flexibility of the assembly system by integrating innovative sensor and controlling strategies. Tsarouchi et al. (2013) utilize a vision-based robot control technique to solve a flexible pick
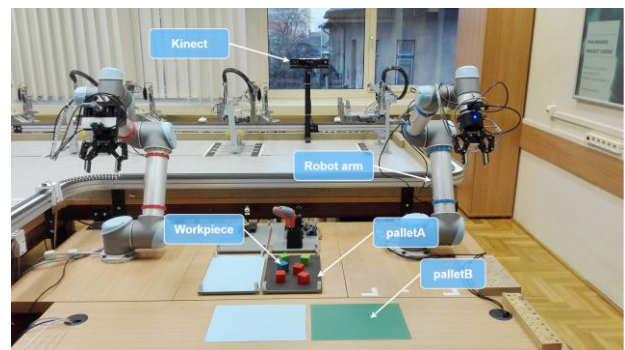

Figure 1. Picture of the *SmartFactory* cell

and place task. Their system uses camera images to determine the position of multiple, randomly placed, similar objects and control the motion of a palletizing robot. Fleischer et al. (2013) utilize visual servoing principles for accurately aligning aluminum space frame structures in a fixtureless assembly. Yu et al. (2017) use camera-based robotized pick and place cell, in the protective glass manufacturing industry, for loading glass pieces of cell phones to grinder machine.

Today, industrial robot programming natively utilizes open loop control strategies. This strategy first plans and pre-programs the movement of the robot, then the controllers execute the synchronized motion sequences. To change the feedforward strategy to a feedback system requires that many aspects of the subsystems of the assembly cell such as robot equipment and industrial IT-systems must change. These requirements call for the implementation of a Cyber-Physical Production System (CPPS). According to networks Monostori et al. (2016), a CPPS consists of autonomous and cooperative elements and subsystems that are connected based on the context within and across all levels of

production, from processes through machines up to production and logistics.

The key factor to the successful sensor feedback system implementation is to "push-down" the micro planning to the cell controller. This planning functions can be implemented if an accurate digital representation of the assembly cell is available. Tsarouchi et al. (2015) proposed a solution that integrates the macro planning both for human and robot operators in an assembly cell.

The goal of every assembly system is to physically realize assemblies that were modeled by their designers (Whitney, 2004). The way to realize assemblies is defined in the assembly process plan. Process planning is an intricate problem with many open and unresolved issues. Because of the complexity of assembly process planning, usually, a hierarchical decomposition methodology is employed to keep the calculation requirements at bay. Traditionally process planning is divided into two steps (Kardos et al., 2017):

1. *macro level plans* specify the operations by assigning resources (like tools, fixtures, workers or cells), giving the sequence of operations, as well as the groups of operations – so-called setups – that will be performed together, by using the same resources;

2. *micro level plans* specify all other details like path, fine movements, exact tooling, and operation parameters necessary for executing the plan in a given production environment.

Macro level planning incorporates primarily Assembly Sequence Planning (ASP), in which a sequence of (expectantly collision-free) assembly operations is computed. If there are more assembly stations on the shop floor, then Assembly Line Balancing (ALB) is also considered, in which the assembly operations (and the corresponding sub-assemblies) are assigned to assembly stations in such a way that station workloads are balanced. The output of the macro level planning is twofold:

• *assembly model* of the assembly and subassemblies. It is a digital representation of what to build;

• *assembly process plan*, which is a digital representation of how to build an assembly.

Many real-life assembly processes—especially when human operators execute the operations—are based solely on the macro level plans. The micro level plans, in this case, are omitted completely, because the fine details of the plan are resolved by the expertise of the human operators. The macro level plan is traditionally represented as a process flow chart or process Gantt chart.

1.1 Problem statement

In the case of robotic assembly cells, the micro level plans are of utmost importance. In this case, the synchronized path of the robots should be planned and programmed either off-line or online before the cell starts working. The micro level plans are traditionally delivered for robot cells as two program files:

1. path information, containing the robot motions in robot program files;
2. state synchronization of robot motions which is defined in the program of the cell controller's PLC.

The biggest problem of the pre-generated micro plans is that they presume accurate and static knowledge of the environment that does not change over time. To ensure the accuracy of the key points of the features of parts, accurate fixture and jig systems are used, and the coordinates of the key points are manually programmed. Clearly, both the accurate (and expensive) fixturing system and the time-consuming on-site teach-in process act against the flexibility of the assembly cells.

The solution detailed in this paper mitigates both the part specific fixture and the manual teach-in requirements by resolving inaccuracy problems online using visual sensor based micro planning. This paper addresses the development of a flexible robotic cell that is capable of online calculating the micro plan based on the visual sensor data for a given macro plan. Furthermore, it executes these operations in a cyber-physical test cell.

This paper presents a cyber-physical system based framework of a robotic assembly cell. This proof of concept aims to improve flexibility by utilizing visual sensor information that is fed back to a digital twin, where micro planning functions such as grasping, and path planning are executed. An application of the framework is demonstrated in a pick and place case study of a physical assembly process.

2. SYSTEM ARCHITECTURE

The robot cell consists of two articulated robots (UR5) equipped with a 2-finger gripper, a force sensor, a distance sensor, a camera, a Kinect sensor, a server computer, and a local workstation (see Figure 1). The system follows the 5C architecture (Lee et al., 2015): it consists of 5 levels following a sequential workflow see in Figure 2.

The *smart connection level* is in direct contact with the environment. This layer is responsible for gathering data in real-time or for implementing an intervening process in the environment. This level includes the robot arm, the gripper, the force sensor, the distance sensor, and the camera.

The task of the *data conversion level* is to extract valuable information from the data. This level is realized with data acquisition units (DAQ).

The cyber level is the third layer, which embodies the *dispatcher* module and the intelligent subsystems such as the *robot controller, distance processing, image processing*, and *gesture processing* units. The dispatcher module connects the aforementioned subsystems. Additionally, through the dispatcher, other entities of the production system can connect to this network, independently from their functional level.
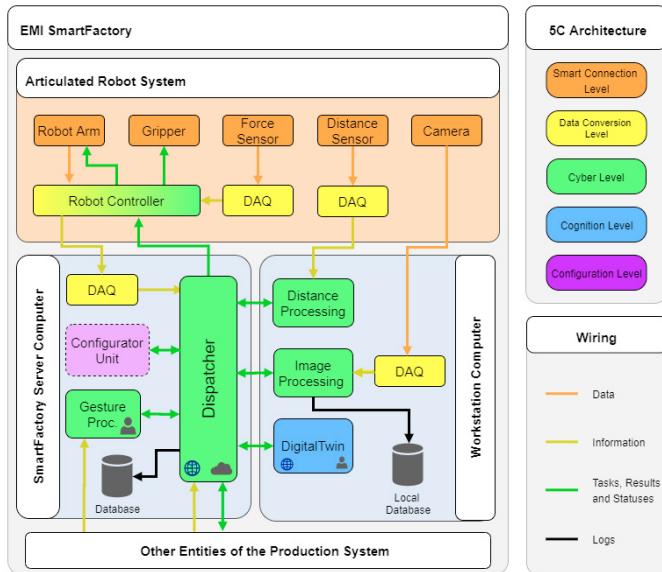
Figure 2. 5C architecture of the *SmartFactory* cell

The *cognition level* is a decision support layer that represents characteristic data of the production system to the user. In this system, the so-called *DigitalTwin* component is responsible for the virtual micro planning of the assembly tasks.

The last layer is the *configuration level* where the supervisory control system runs. This service supports self-configuration for resilience, self-adjustment for variation, and self-optimization for disturbance. This level is yet to be implemented in the test cell.

3. CASE STUDY

The case study, developed in the *SmartFactory* cell, is based on abstract pick and place operations. The final assembly is a pyramid of 6 colored cubes. The inputs of the case study are:

- model of the final assembly;
- macro plan that defines the sequence of tasks.

The system recognizes the part position and orientation (henceforth called as posture) that are randomly distributed on the input pallet (*palletA*) using an eye-in-hand camera. The postures of the parts in the digital twin are updated from the postures calculated by the image processing module.

The final postures of the parts are defined in the assembly model which is extracted from the macro plan. Grasp planning and path planning are executed in the digital twin. The final micro plan is then formatted to a text message and sent to the dispatcher module. Next, the finite state machine of the dispatcher module executes this plan and builds the assembly on the output pallet (*palletB*). The implemented sequence is shown in Figure 3.
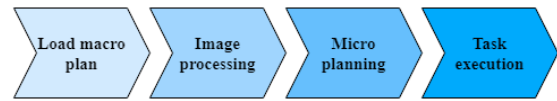

Figure 3. Sequence diagram of the case study

3.1 *DigitalTwin*

The digital twin of the work cell is modeled as a linkage, which is capable of capturing the geometric and kinematic relations of the static and moving objects (Horváth and Erdős, 2017). A linkage model is utilized to represent the assembly as a kinematic graph where the edges of the graph define the transformation between the part's reference frames, while the nodes store the geometry of the parts (see Figure 4).

A digital twin is generally used for visualization and online micro planning. Having organized every component of the cell into a kinematic graph, it is possible to calculate transformation between the reference frames of any two parts. The postures of the components are defined with an appropriate parametric expression. These parameters are continuously updated by the processed sensory input. Thus, the linkage model is capable of synchronizing the posture of every component with their real posture, based on sensor information or joint positions, which were acquired from the robot controller.

3.2 Macro plan

The macro plan specifies the sequence of tasks to be executed in order to create the final assembly. The task defines one high-level operation and the resources required to execute the given operation. Two kinds of resources are considered here: the workpiece and the robot. Only one type of operation called pick and place operation is used in the case study. That specific operation has been chosen as this is used in almost every assembly plan. Accordingly, a schema incorporating the required data content of both the macro and micro plan has been defined (see in Figure 5).
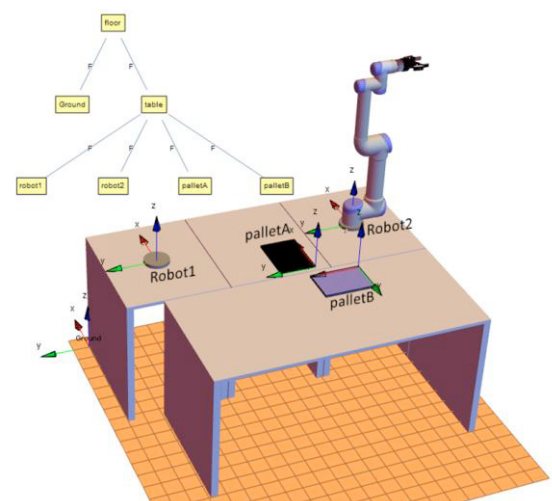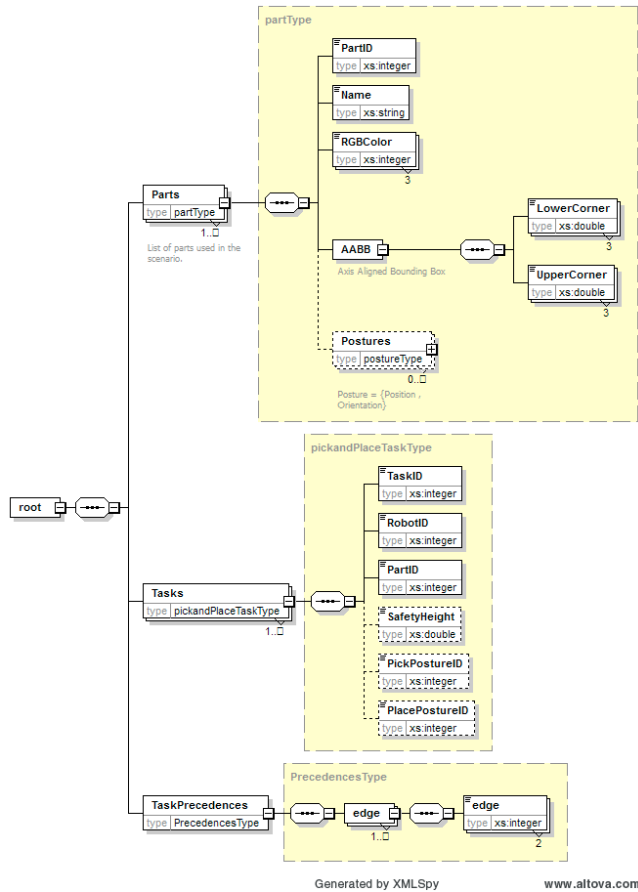

Figure 4. Posture frames in *SmartFactory's* linkage
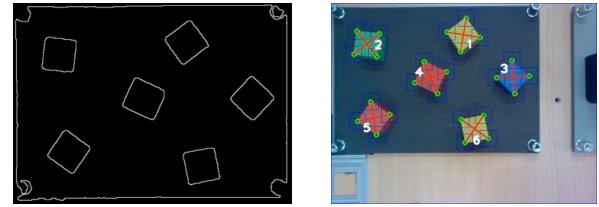
Figure 5. Schema for the macro and micro plan

Figure 6. Image-based posture recognition. Contour detection (left), and center point detection (right)

4. geometry supervision (rejection of the objects with incorrect geometry);
5. postures (center points and orientations) calculation using corner detection;
6. color determination (*RGBColor*);
7. transformation of the image coordinate system to the *Robot2* coordinate system (see Figure 4).

3.4 Camera calibration

Here, by camera calibration, the *Robot2* coordinate transformation is meant which unique to the given working environment. A semi-automated calibration process was constructed (to this eye-in-hand camera set up) in order to calculate this transformation. Four, differently colored workpieces are picked and placed on the pallet at predefined points. Afterward, a picture is taken and processed. With the knowledge of the color sequence, the postures of the objects in the image and in the *Robot2* coordinate system can be matched and the transformation can be calculated. Storing the transformation matrix, this calibration process needs to be performed only once in any new working environment.

3.5 Path planning

The pick and place operation uses a simple path template shown in Figure 7. This path can be generated if the following three parameters: tool-center-point (TCP), *Pick Posture*, *Safety Height,* and TCP place postures are known. TCP pick posture is calculated from the part's posture, which was obtained during image processing. The TCP is determined from the posture of the part, which was specified in the macro plan (*placePostureID* see on Figure 5).

The workpiece related data is stored in the *Parts* element. It requires the *PartID*, the *RGBcolor,* and the axis aligned bounding box (*AABB*) information as mandatory data. The optional *Postures* data specify a part related posture (position and orientation). Posture data can indicate the following information:

- the final position of workpieces (assembly model);
- the grasping posture on the workpiece;
- the pick posture of the workpiece.

The *Tasks* element associates the workpiece, robot, and operation, while the *TaskPrecedences* element stores the task sequencing information.

3.3 Image processing

For adaptive environment sensing the pallet and the workpieces must be detected in order to determine their postures and colors which are needed during micro planning. The steps of the image processing are depicted in Figure 6 as follows:

1. detection of the arbitrarily rotated pallet;
2. background subtraction using flood fill algorithm and contour detection;
3. objects segmentation (transforming sets of points to objects' curves);
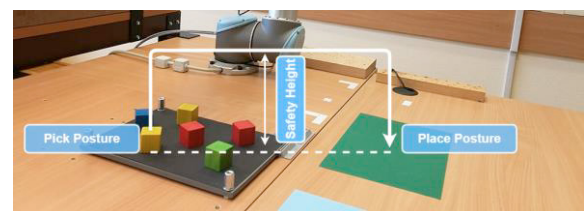

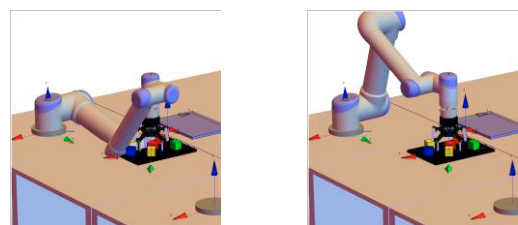Figure 7. Pick and place path template

Figure 8. A not feasible (left) and a feasible (right) pick configurations of the first workpiece

Having obtained the postures of the TCP, the inverse kinematic problem is solved, and the feasible robot configurations are selected. Figure 8 depicts the configuration 1 and 2 for the pick posture of the first workpiece. The first configuration is not feasible in the actual cell because in this configuration the robot would collide with the table. As a final step, the command of the parametric pick and place path is built using the TCP pick posture, safety height, TCP place postures, and the configuration selector vector. This command is considered as the micro plan of a given task (see Figure 9).

3.6 Task execution

The finite state machine implemented in the dispatcher module (see Figure 2) is responsible for executing the task graph, which is defined in the macro plan. The robot receives and sends messages in two individual sockets using TCP-IP protocol. A message that is received from the dispatcher contains the parameters of one pick and place operation, which is the micro plan of the task. The robot sends back status messages to the dispatcher such as a command received, a task started, a task finished, or an unexpected malfunction happened. The finite state machine watches these status messages and starts a new task as the sequence of the tasks is defined in the master plan.

4. CONCLUSIONS

The paper suggested a new framework to build flexible robotized assembly cells using visual sensor feedback. The framework splits the macro and micro planning into offline and online processes. It is argued that the flexibility of the work cell could be enhanced by executing micro planning functionality in the digital twin based cell controller online. Further possible improvements include collision detection and advanced path planning in the micro planning level, extending the set of operation features to other types of operations (screwing, gluing, etc.), and the utilization of a depth sensor for posture recognition.
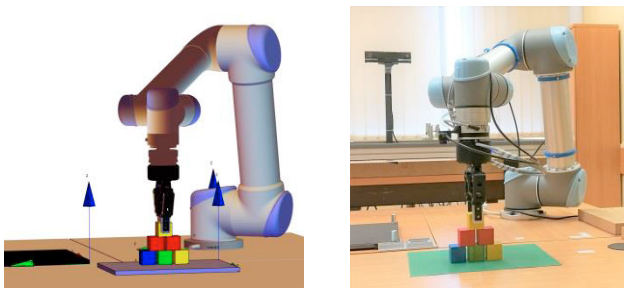
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Figure 9. Placing robot configurations for the last cube in simulation (left) and in reality (right)

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