Competitive high variance, low volume manufacturing with robot manipulators

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Abstract— **Competitive robotized manufacturing of high specter variance, low volume product lines represents market opportunities for manufacturing companies, but cost-efficient production is challenging. In this paper, we present two main industry use cases which represent key challenges to be solved for cost-efficient low-volume, high-variance production. The use cases are found in collaboration with three manufacturing companies. We identify and describe these challenges which include perception and manipulation with shiny/high-reflectivity parts, human-machine interfaces for robot reconfiguration and calibration between simulated and real-world environments. In this paper, we present new methods for meeting these challenges: machine vision for handling sensor data with low quality in robot manipulation, automated robot programming based on CAD-models and automated calibration. Moreover, we implement and demonstrate the methods on the two identified industry use cases for robotized assembly.**

Keywords—Industrial robots, robot programming, CAD, perception, manufacturing, industry challenges

I. Introduction

Manufacturing of low- to medium-sized volume of products with high variance specter represents a significant opportunity for manufacturing companies. However, cost-sensitive markets may require that companies have a high degree of automation in the production processes to succeed [1]. To this end, relevant use cases from the industry, challenges and opportunities with novel robot technologies are the topics of this paper (see Fig. 1). This paper summarizes key results from a 4-year project on robotized manufacturing of high-variance parts called KOPROD[1]. The results in this paper come from collaboration between three Norwegian manufacturing Small and medium-sized companies (SMEs) and a research organization in KOPROD.

Automation of assembly processes generally require complex solutions composed of different technologies that cooperate in a uniform interaction [2]. Development of such systems involves time-consuming programming of systems made for a specific assembly process. Building, running and making changes due to frequent product change-overs require high skilled employees with special expertise of robot programming, sensor technology etc., – competencies that often are lacking in small and medium sized enterprises (SMEs) [3].

SMEs within manufacturing may have a lower level of automation and robotic competence among their employees than bigger companies and industrial enterprises and followed by that, a higher threshold for including robots in their process operations. There is also a shortage and high cost of skilled workers [4]. In addition, their manufacturing processes often consist of short production runs, frequent change-over and short product life that results in increased use of resources in order to adapt to changes in products. Small and medium sized production volume in a cost sensitive market makes the situation even more challenging [5].

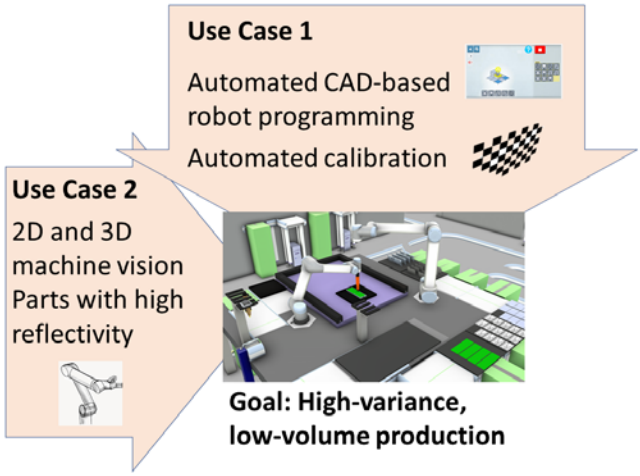

Fig. 1: The use cases in this paper target key challenges with enabling competitive high specter variance, low volume manufacturing with robots.

For many SMEs with small scale production and large product variations, automation of assembly processes is out of range due to lack of the technical knowledge and competence requirement. With a robotized product assembly cell, a robot may be used to handle each component of a product that may vary in size and shape. The robot must have information about the position of each part to be picked, and where to be placed, and while moving the components, obstacles must be avoided. It may also be necessary for the system to "see" both the position and orientation of the part before it is grasped and the position and orientation of the delivery [6]. High reflectivity of the parts' surfaces (i.e., they are shiny) makes the detection operation more difficult.

There are several important developments for robots in assembly processes. E.g., an autonomous dual-arm mobile robot system was presented in [7], while [8] details a robot system solution targeted toward Industry 4.0. Moreover, [9] includes an approach to safe workspace monitoring in assembly operations.

[1] https://www.sintef.no/prosjekter/koprod/

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Computer-based simulation programs are used to aid robot programmers to simplify robot programming [10, 11]. But common for these simulation programs is that a human programmer uses toolboxes to sequence and parameterize programs manually. For low- to medium-sized volume there is a need for automated programming of sequence and parameterization to ensure cost efficiency.

3D object recognition and pose estimation is of great importance within robotic manipulation (see, e.g., [12] and [13] for relevant surveys of the state of the art within this area). In the industry, many commercial systems are available for automating assembly processes with machine vision. They range from fully integrated [14, 15] (vision, robot, gripper and software) systems to custom ad hoc systems provided by integration companies (using off-the-shelf sensors, robots and software) [16, 17]. These systems solve the automation task in many cases, but applications involving product components with high-reflectivity surfaces still pose a challenge because current 3D sensors (structured light, stereo cameras, Time-of-Flight cameras) often provide low quality data (missing or incorrect) on these surfaces. In recent years several manufactures began to address this problem in different ways [18, 19], but a general solution has yet to be found.

In this paper we present two industry use cases relevant for production of high-variance specter products and we identify key challenges for robotic assembly for such use cases. Moreover, we present novel technologies for meeting the identified challenges. These include CAD-based robot programming, auto-calibration of robotic work-cells, as well as sensing and perception for automated manipulation of shiny/high-reflectivity parts. Moreover, we present experimental results that target the needs of the above-mentioned use cases of high-variance products. To this end, we demonstrate the results on two use cases where we in Use Case 1 focus on intuitive robot programming and in Use Case 2 focus on pick and place of small, complex parts with shiny surfaces.

The remainder of this paper is organized as follows. In Section II, we present the KOPROD project, industry challenges and use cases. In Section III, we present some of the main methods and technologies developed in the KOPROD project. In Section IV we provide experiment results and in Section V we conclude on the work and give input to further work.

II. THE KOPROD PROJECT AND INDUSTRY USE CASES

In this section we first briefly describe the KOPROD project and the focus areas of the industry partners. Then, we outline challenges within manufacturing and describe two use cases targeted at addressing these challenges.

A. The KOPROD Project and Industry Partners

The main objective of the KOPROD project (2017-2020) has been to develop methods and technical solutions in an industrially relevant environment, for future competitive production of complex, low and medium volume products against cost-sensitive markets. Automation has helped manufacturing companies increase productivity and reduce costs for decades. The three manufacturing companies in KOPROD, Mjøs Metallvarefabrikk AS, Sandvik Teeness AS and Tysse Mekaniske Verksted AS all have great opportunities within cost-sensitive markets, where future competitiveness depends on increased automation of low and medium volume production of products with a wide range of component variants.

In this project we focus on the following activities of the manufacturing partners:

- Mjøs Metallvarefabrikk AS produces vacuum pumps. Their main client is Jets which focus on vacuum toilets, discharge systems and condensate removal systems in supermarkets and has annual sales of more than NOK 400 million. The pumps have a range of small and medium-sized parts, some of them shiny, which needs to be assembled with high precision.
- Sandvik Teeness AS produces Silent Tools™ – a family of tool holders for turning, milling, boring and drilling. The tool holders are designed to minimize vibrations through a dampener inside the tool body. The assembly process of these tools includes very small (millimeter-size) parts, to small (centimeter-size) shiny parts, to very large (meter-size) parts.
- Tysse Mekaniske Verksted AS produces a large range of different trailers for motorized vehicles. The trailers can be several meters long. The parts in the assembly process range from centimeter-size to several meters.

B. Challenges in the Industry

The combination of cost-sensitive markets and products produced in low- to medium-size volume with high-variance specter constitutes a challenge for the manufacturing industry as a whole. We have identified some of the key challenges that need to be tackled in order to let manufacturing companies easily adjust production and cut turn-around times in switching between different varieties of a product. Thus, this aims to contribute to bridge the gap between market opportunities within the aforementioned manufacturing tasks and available cost-efficient automation solutions. These challenges include the following aspects which are addressed in this paper:

a) Insufficient data quality of current 3D sensors on shiny parts lead to difficulties with machine vision for robot manipulation.
b) Machine learning approaches for object detection and pose estimation require a lot of training data which is not freely available for most SMEs.
c) Complicated human-machine interfaces which require substantial reconfiguration or time-consuming reprogramming of the system when new products are introduced, or processes are changed.
d) Efficient robot programming by automated creation of assembly sequence with product-model as input and usage of computer-based simulation software
e) Automated calibration of object location between a simulated environment and real-world environment.

C. Industry Use Cases

In order to develop and demonstrate technologies for automated production with robots that meet the abovementioned challenges, we have identified two main use cases. The production processes of all the manufacturing companies in KOPROD were analyzed in terms of which challenges they represent. Based on these analysis two main use cases from the companies were selected. These two were chosen due to that they represent actual needs of the industry partners and together span the challenges identified in Section II.B. The uses cases are:

- **Use Case 1**: Robotized assembly of vacuum pump parts.
- **Use Case 2**: Pick-and-place of shiny parts.

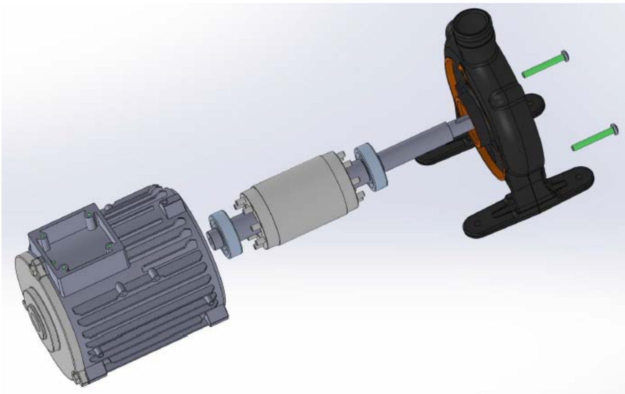

Fig. 2: Parts to be assembled on a vacuum pump, motor housing, rotor with preassembled bearings, a flange and to bolts (Use Case 1).

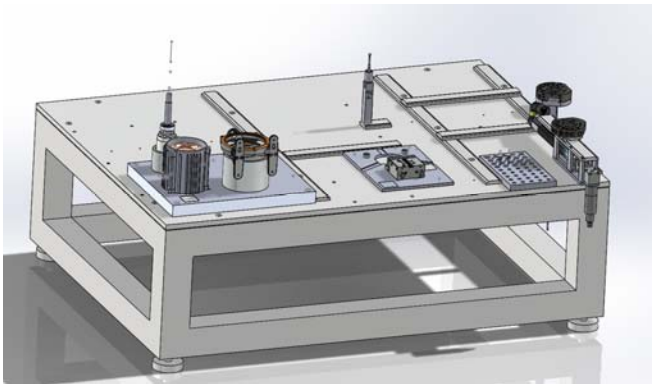

Fig. 3: Initial object locations (Use Case 1).

The use cases are further detailed below.

1) Use Case 1: Robotized Assembly of Vacuum Pump Parts

In Use Case 1 we use a specific product to demonstrate how to structure a product-model into an assembly process. The process includes a motor housing, rotor with preassembled bearings, a flange and to bolts. This translates to five pick and place tasks, where placing is force controlled, and two bolting tasks. We have the following information available: three CAD-assemblies, the final product (Fig. 2), initial locations of each product component and definition of how components are placed in a robot-gripper.

2) Use Case 2: Pick-and-Place of Shiny Parts

In Use Case 2 we address pick-and-place and assembly of small (millimeter and centimeter-sized) shiny metal parts included in tools for milling, boring and drilling. Specifically, these tools include a cutting head and a nozzle. See Fig. 4 for a selection of cutting heads and nozzles. A nozzle needs to be pushed into a hole in a cutting head. Both the cutting heads and nozzles vary in shape and size. In order to robotize the assembly process, the cutting heads should not need to be made available in a structured manner. E.g., they should reside in an open box and be scattered out on a table (the latter was chosen in the KOPROD project). The nozzles can be made available in an organized manner on a pallet.

III. Methods and Technologies

In this section, we describe the technologies developed and implemented in order to address the need for robotized assembly operations in product liens with high variance, and thus demonstrate the use cases described in Section II.C. The technologies are as follows:

- Robproc [20] – a methodology and software for converting product models to a robot program with minimal programming skills needed from product developer or operators.
- Calibration – software in Robproc to handle the transitions from a virtual environment to a real environment automatically using standard metrology methods with a touch triggered probe. But in this case the trigger-probe is mounted on a robot instead of a metrology machine.
- Sensing and perception for shiny parts – i.e., blank parts with high reflectivity which may often give poor sensor data quality for machine vision methods used for robotized assembly.

Fig. 4: Examples of shiny parts relevant for pick-and-place operations in Use Case 2. Top row: cutting heads. Bottom row: nozzles.

A. Robproc

A new method, Robproc, uses CAD models as input to produce executable robot program. Connection to a robot from robproc are a minimized interface exposing only basic robotic skills, such as motion commands, digital IOs and force control. Currently there is interfaces to KUKA and ABB. The aim of the method is to lower the entry level of automated solutions in SMEs, give faster change-over and tuning of the processes with less need for robot expertise. To achieve this, the theory is that by minimizing required programming skills of product developers and operators, one can increase the usage of advanced robotics in SMEs. Robproc is created as a framework written in the Python programming language.

1) Product design and assembly planning

Design of products is important in automation; therefore, this approach relies on a strong focus on design for automation. Alongside the actual design it is important to define assembly sequence, one method of doing this is to manipulate the tree structure of a CAD-assembly. The components can also be annotated with special tags. These tags are used later to generate actual tasks to be performed, e.g., if force control is needed during placing of a component. For each product a minimum of three separate CAD-assemblies are required: final product, initial locations of each component in the final product and gripper definitions. If an assembly operation requires multiple robots, this is handled by adding extra gripper definitions, but this causes some limitations in regard to which robot can pick which component. Also, there is no support for the robots to collaborate, meaning all tasks are done in sequence and not in parallel or in a state where multiple robots can collaborate on a task.

2) Task building and connectivity

To build actual tasks needed to complete the assembly of components, the CAD-assemblies created for a product are loaded into a module called a builder. The builder module implements a minimalistic interface to three different CAD-systems: SolidWorks, SolidEdge and NX. The module iterates over the assembly sequence and generates a list of tasks for a robot to execute from annotations, i.e. pick-and-place task. But in addition to this there are automatically generated tasks for path-planning, this is because one only denotes start and end position in CAD, but the path for moving a component from start to end needs to be defined. The tasks are classes in a Python library and are as standardized as possible. Robproc searches through these classes to match each task named in CAD to a given class. Inside these classes there exist a call method that calls the relevant robot functions, e.g., a pick task can be as simple as a linear motion to a component target. Robproc makes sure that the robot is in a correct position when the pick task is executed. When the list of tasks is completed it can be run in a simulation program where collisions are checked for. If problems are detected one can review the design. Else, this task list can be connected directly onto physical equipment from Robproc.

3) Visualization

The entire assembly process can be visualized in both an augmented and virtual environment by using graphical engines like Unity.

B. Calibration

Automatic assembly processes are often critical due to high precision in joining of components, or in grasping or placement position at critical locations like fixtures and jigs. These requirements demand for a calibration process updating the robot program with exact positions of the critical positions. Calibration of different coordinate frames may be performed either as an initial cell calibration, after replacement of i.e. part trays or for every N cycle.

We propose a calibration method that is divided into two steps: rough and accurate calibration. The difference between them is the expected accuracy and initial object location accuracy needed. In step 1 we find the rough object position by using QR-codes. These codes can store object information and can be used, with a stereo camera system mounted on the flange of a robot, to detect rough object position. This method requires that object location accuracy is within field of view for the stereo camera, typically in the range 0.5 m-1 m from the camera. As Step 2 – for turning the rough position into an accurate position – we use a trigger probe mounted on a robot to do standard metrology methods. The result is an accuracy acceptable for robot assembly. By using a robot as metrology machine, all objects are calibrated to the coordinate system of the robot, thus we can neglect the absolute accuracy of the robot. Documentation of the accuracy of this approach is a subject for further work, but in general one can expect an accuracy smaller than 1 mm and at best 0.1 mm.

C. Machine vision with shiny objects

In this paper, we specifically address machine vision methods for handling product components with high-reflectivity surfaces. We tested and implemented several approaches to detect precise location and orientation of such parts to be assembled (i.e., the components of a product to be manufactured). Our final solution meets the following requirements:

- Parts come in a variety of shapes and sizes (about 300 varieties).
- CAD models for the parts are not available (for Use Case 2, not Use Case 1).
- Limited training data for machine learning system.

In order to meet the above requirements and facilitate that a robot can do pick-and-place, we have developed a method for object detection based on fusion of 2D and 3D methods for RGB-D-data (i.e., color and depth data). First, we do pattern detection of common areas for the parts in 2D to find an approximate position of a part to be picked by the robot, then we employ 3D methods (fitting geometrical primitives to point clouds) to check the estimates from the 2D method and find the 3D pose of the part. To this end, we employ RANSAC for plane detection. This approach to fusion of 2D and 3D methods allows us to detect object orientation with high accuracy given incomplete 3D data due to shiny surfaces of the parts. In addition to the above approach, we also employ monochrome 2D data for high-precision localization of a part. This latter approach is based on circle-detection. Our system uses Intel RealSense D415 RGB-D and Basler 2D cameras for imaging.

As mentioned, we have also implemented and tested other approaches. To this end, we have implemented a machine

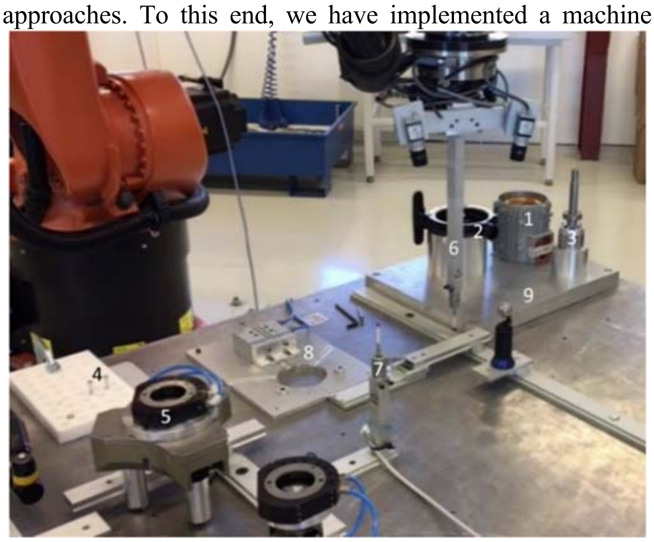

Fig. 5 Setup for Use Case 1. (1) the motor housing, (2) a flange, (3) a rotor with preassembled bearings, (4) a fixture with two bolts, (5) the motor housing gripper, (6) the calibration probe, (7) a fixed probe, (8) assembly fixture and (9) the assembly kit fixture.

learning based approach by using filter banks and gradient boosting (XGBoost [21]) to detect the position and orientation of product components. With the high-variance specter of parts in the production of the manufacturing companies in this study, it was challenging to gather a sufficient amount and variety of test data for the machine learning algorithms. To this end, the 2D-3D fusion-based approach described above gave better results.

IV. Experimental setup and results

A. Use Case 1: Assembly of a Vacuum Pump

1) Use Case 1: Approach and Experiment Setup

Use Case 1 has been developed to demonstrate utilization of the robot programming method, Robproc, including calibration and trajectory planning, in a real environment. Robotic assembly of the first four parts of a pump were selected to represent the first industrial case in this project (i.e., Use Case 1). This assembly process includes a motor housing, rotor with preassembled bearings, a flange and two bolts. Recall Fig. 2 for an illustration of the product to be assembled, and see Fig. 5 for the robot cell setup. To demonstrate different levels of calibration and design, two different rotors were used, one original and one with an extra guidance chamfer. The difference in rotor has no effect on the automated robot programming, but has an effect on what execution and calibration level are needed. All calibration routines are created as annotation in a respective CAD-model.

In order to use a robot for automatic assembly, we generally need to know where the parts to be assembled are located and where they should be put. Hence, the position of relevant objects in a robot cell (e.g., jigs, etc.) must be known (e.g., measured). In order to speed up assembly it can be advantageous to do as few measurements as possible for each assembly operation. However, too few measurements can lead to too low accuracy in assembly operations and thus the assembly operations may fail. To this end, we test and evaluate five different experiment setups with varying degree of measurements and calibrations for Use Case 1. All experiment setups include calibration of jigs and blisters and this is done automatically with a probe as described in Sec III.B, but calibration of gripping accuracy (i.e., the accuracy of the actual gripper-relative location of a part in a gripper)) and placing accuracy (i.e., the accuracy of the actual position that a part has after having been placed somewhere e.g., in a jig) is optional and not included in all the setups. To this end, the following experiment setups are defined for Use Case 1:

1. Normal run (i.e., calibration of jigs and blisters, but not gripping and placing accuracy) both modified and original rotor, with only force-monitoring of the tools of the robot for safety.
2. Normal run with both modified and original rotor, with force control of the tools of the robot.
3. Run where place position of motor housing is calibrated, only original rotor.
4. Run with measuring of rotor in gripper (using a fixed probe – see Fig. 5), only original rotor.
5. Combination of the measuring done in setups 2 and 3, without force control and tested for both rotors. The result from this can be used to state the accuracy of the calibration routine.

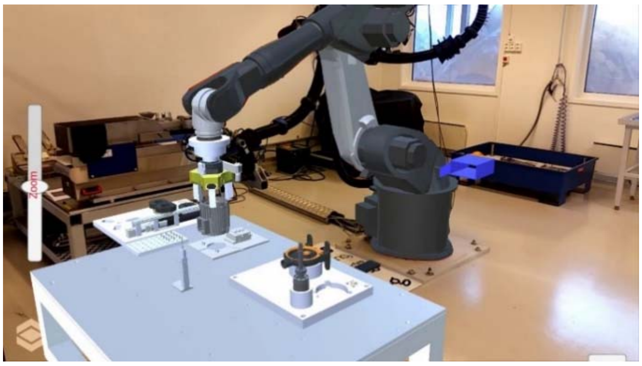

Fig. 6. AR-visualization of normal run in Use Case 1.

The normal run was be visualized with the use of augmented reality (AR), see Fig. 6.

2) Use Case 1: Experiment results and discussions

Each of the proposed setups was tested, using a lab facility consisting of a KUKA robot, Basler Cameras and Renishaw probes as shown in Fig. 4. The Basler cameras is used to detect QR-codes for approximate calibration of object locations. Setup 1 failed for both rotor types; this is related to position inaccuracy leading to too great force values when placing the rotor into the housing. Setup 2 was successfully achieved for the modified rotor. This was related to the chamfer, because this created a less demand on accuracy and the force control could guide it to its correct position. For the original rotor, the robot stopped due to too great force values upon first entry of the rotor into its housing. This again was related to inaccuracy in position. Setup 3 and 4 failed for the same reasons as in setup 2. Setup 5 was successful for both rotors; this comes from the fact that everything was measured such that the only inaccuracy was the robots repetition accuracy. The tolerance for inserting rotor into the housing is +- 0.25 mm, this means that since the assembly is done successfully without force

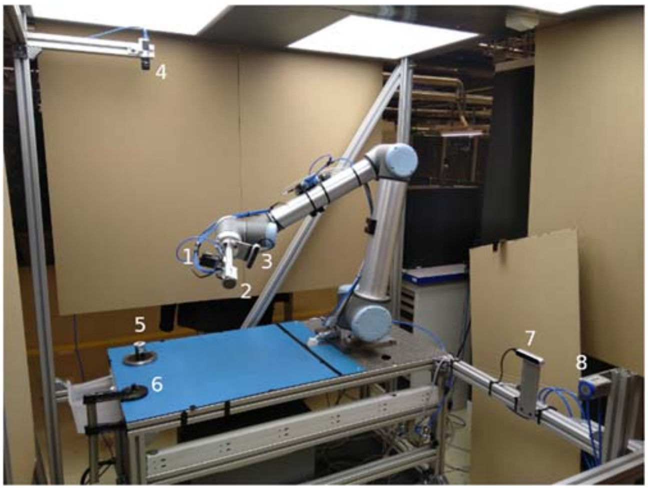

Fig. 7. Setup for Use Case 2. Components include (1) a two-finger gripper for handling nozzles, (2) a magnetic gripper for handling cutting heads, (3) a RealSense 415 camera – all three mounted on a UR10 robot manipulator from Universal Robots, (4) a Basler monochrome camera for precision estimation of 2D position and orientation of a cutting head held by the robot's magnetic gripper, (5) a jig to fix the cutting head's position and orientation for parts assembly, (6) a pallet for nozzles, and a reorientation station for cutting heads. The reorientation station is composed of (7) a Realsense 415, and (8) a magnetic gripper. All grippers are actuated by pneumatics.

control, one can argue that the accuracy of the calibration method is less than 0.25 mm. This indicates that one can automatically create programs using different approaches with respect to design and calibration to achieve the same result, without changing anything but the CAD-models. This shows that automated programming is doable, but to prove the simplicity, more tests must be performed by relevant end users.

B. Use Case 2: Pick-and-Place of Shiny Parts

1) Use Case 2: Approach and Experiment Setup

The objective of Use Case 2 was to mount a nozzle into a cutting head (See Fig. 4 for examples of cutting heads and nozzles) – both parts had shiny surfaces. To automate this process with a robot arm we chose the robot cell configuration and automation approach as shown in Fig. 7 and Fig. 8 . The details of the robot cell are described in the caption of Fig. 7.

The process for automatic pick-and-place proceeded as follows. An operator spread several cutting heads on the table and filled a pallet with nozzles. The positions of cutting heads were detected using a combination of RGB and depth data and each part was picked by the robot using the robot-mounted magnet gripper. If a cutting head could be picked by attaching the robot-mounted gripper the top of the part (a striped side with 3 holes and a cavity for placing the nozzle), we detected an exact position of the center cavity and the holes of a picked part (using a monochrome Basler 2D camera with a macro lens) and placed the part into the jig for assembly. Then the robot picked a nozzle with a corresponding diameter and pushed it into the cutting head in the jig.

If a cutting head could not be picked from its top, then it was picked by a side and the exact orientation of the part was detected by a 3D camera at the reorientation station. The part was placed into the reorientation magnetic gripper such that the top was pointing upwards. Afterwards the robot picked it by the top and proceeded to detect the exact position of the cavity as above.

Robot control and vision have been implemented using a modular Python-based approach, allowing an easy rearrangement of the robot cell setup through a central configuration module and an assistant module to calibrate the cameras' intrinsics and extrinsics relative to the robot.

2) Use Case 2: Experiment results and discussions

As described previously, and can be seen in Fig. 8, the process of assembling the cutting heads and nozzles involved several pick- and place-maneuvers and orientation detections.

We performed more than 30 test runs with various parts in relatively controlled lighting conditions. The complete system allowed for correct part assembly in 90 % of the test runs. For the remaining 10 % the main challenges were mostly of mechanical nature. We detail the challenges further in the following. If the cutting head was not attached stably on the magnetic gripper on the robot (see "2" in Fig. 7) it could change its orientation due to rapid robot movements and gravity. This was especially a problem when instability happened during the motion of the robot between detecting the head orientation (at camera 7 in Fig. 7) and placing it in the stationary magnet (8 in Fig. 7, II in Fig. 8). In this case, the part could be placed in the reorientation magnet in such a way that its top could not be detected using the robot camera (3 in Fig. 7) and so it could not be picked from its top. Some of

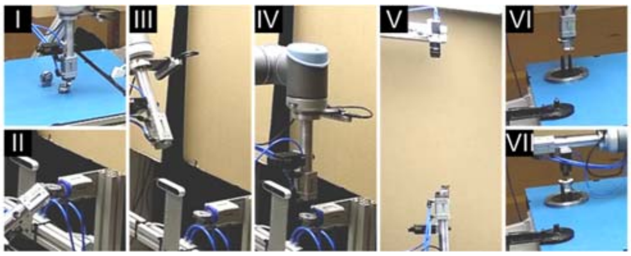

Fig. 8. Process steps of assembly: (I) Pick head on table, (II) place in stationary magnet for reorientation, (III) find orientation, (IV) pick, (V) find exact heads coordinate frame, (VI) place precisely in assembly jig, (VII) assemble with nozzle.

these cases can be solved by improving the design of the robot cell to allow wider range of robot movements.

V. Conclusions and Further Work

In this paper, we have presented two main industry use cases within low-volume, high-variance production and identified key challenges that need to be met to enable cost-efficient production. Moreover, we have developed and implemented methods for robot perception in manipulation of shiny product parts (i.e., with high-reflectivity), automated robot programming based on CAD-models and automated calibration. We have tested the proposed methods in experiments which targeted the two identified use cases. The results show that perception algorithms allowed for automated manipulation of shiny parts, but there were challenges with the mechanical handling of such parts with a magnetic gripper. The different runs for automated programming described in this paper show that there are many different ways that a user can set up the Robproc system in order to achieve the same result, and this can potentially be a challenge for the intended user of the method. There is therefore a potential for smarter methods to increase the automation level of the Robproc method. This is a main focus in further work, but it is also interesting to evolve the method to support more complex tasks and collaborative robots. Furthermore, testing with relevant end users is needed to highlight potential difficulties with using the Robproc method. Further work to be considered also includes the mechanical setup for handling parts in Use Case 2.

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