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Research-based teaching in Digital Manufacturing and Robotics – the Digital Factory at the UAS Technikum Wien as a Case Example

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Abstract

Given the proceeding digitization in manufacturing, technical universities are facing an increasing demand to study the technical innovations associated with smart manufacturing concepts in their laboratories and learning factories. Moreover, they need to transfer research insights towards teaching. The thematic spectrum is enormous – starting with production technologies, via robotics and mechatronics, M2M-communication and security, up to the virtualization of processes and modern algorithms, e.g. machine learning. In this context, we explain the concept of the Digital Factory at the University of Applied Sciences Technikum Wien. Further, we present two exemplary use cases and conclude with current findings regarding learning factory concepts.

Keywords: Digital Learning Factory; Virtual Reality in Robotics Education; Machine Learning in Robotics Education

1. Introduction

In many production areas, digitization has become indispensable. There are numerous examples of this, starting with the networking of individual machines, followed by a number of practically proven applications (e.g., smart maintenance), and ending with still research-intensive autonomous robot solutions. The technological basis of such innovative applications is diverse – whether hardware-driven (e.g., sensor technology) or software-driven (e.g., artificial intelligence) [1,2]. Accordingly, technical universities and comparable institutions face an increasing demand

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to study the technical innovations related to smart manufacturing in their laboratories and learning factories: first, they need to explore, operationalize and further develop technologies and respective applications. There are different focal points: while some schools are research-intensive and also conduct fundamental research, others have a focus on applied research. At most universities, this also influences the educational emphases in the course of research-led teaching. Second, research-based education needs to be continuously updated. Thus, teachers must either do research themselves and/or, via continuous, research-oriented lecturer training, elaborately familiarise themselves with the latest research achievements. This includes teaching materials and practical equipment for laboratory exercises [3,4].

Further, educational and research institutions need to continuously convert research findings into practical use cases and to deploy the insights in the course of research-driven teaching. The thematic spectrum is enormous – starting with production technologies, via robotics and mechatronics, M2M-communication, security issues, up to virtualization, business processes and the use of modern algorithms, especially machine learning [1,2,5]. This brings not only technical challenges, but also organizational issues: for example, the question arises which scientific fields are involved – typically robotics, mechatronics, automation technology, but also mathematics, statistics and informatics. As already seen in the term "mechatronics", the delimitation will often not be possible in terms of precision, as organizational responsibilities might try. What is needed is interdisciplinary cooperation. The same applies to non-technical questions within technology application and impact assessment: here, labor-sociological aspects and ergonomics, data security and protection, ethical considerations or economic calculations (to name only a few) play a major role. What is needed is interdisciplinary research, curriculum design and teaching orientation [3].

Thus, this contribution first explains the concept of the Digital Factory at the University of Applied Sciences Technikum Wien (UAS TW) as a vivid example for interdisciplinary higher education in robotics and smart manufacturing. Subsequently, two recent educational Digital Factory use cases are shown: the application of virtual engineering and machine learning. The discussion refers to various dimensions – from technical concepts including implementation aspects in a laboratory situation towards questions concerning teaching and didactics. The remainder of the paper is as follows: section 2 introduces the UAS TW Digital Factory. Section 3 presents the two case examples. Both, machine learning and virtual engineering, have positive impacts on manufacturing flexibility [6] and are therefore important in industrial engineering and educational practices (e.g., online-teaching). Section 4 provides a short conclusion.

2. The Digital Factory at the University of Applied Sciences Technikum Wien

This UAS TW Digital Factory operates with ~15 industrial robots from different manufacturers. To cover a wide variety of smart manufacturing topics, the robots are configured according to typical factory scenarios in an exemplary assembly process, including virtual and augmented reality applications. In addition to the "industrial" factory (hard- and software according to industrial standards), UAS TW has set-up a miniaturized digital factory ("Mini-Factory").

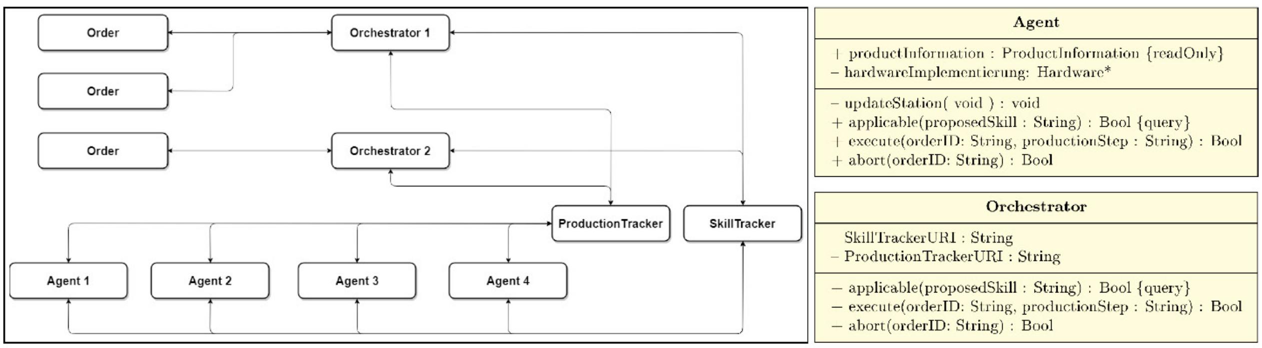

Fig. 1. Communication architecture of the UAS TW Digital Factory.

Both educational factories share the same communication architecture (Fig. 1), data model and system architecture. The data model is designed for a decentralized production where it is easy to integrate new machines by implementing the given interface. The production system consists of production machines (agents), components that collect the capabilities of these machines (skill-tracker) and components, that allocate production orders to available machines (production-tracker). The Mini-Factory consists of self-designed 3D-printed and laser-cut mechatronics and robotics stations. Thus, it is portable (e.g., for workshops). Due to the small size and low voltages, there is a significantly lower safety risk, compared to the industrial factory.

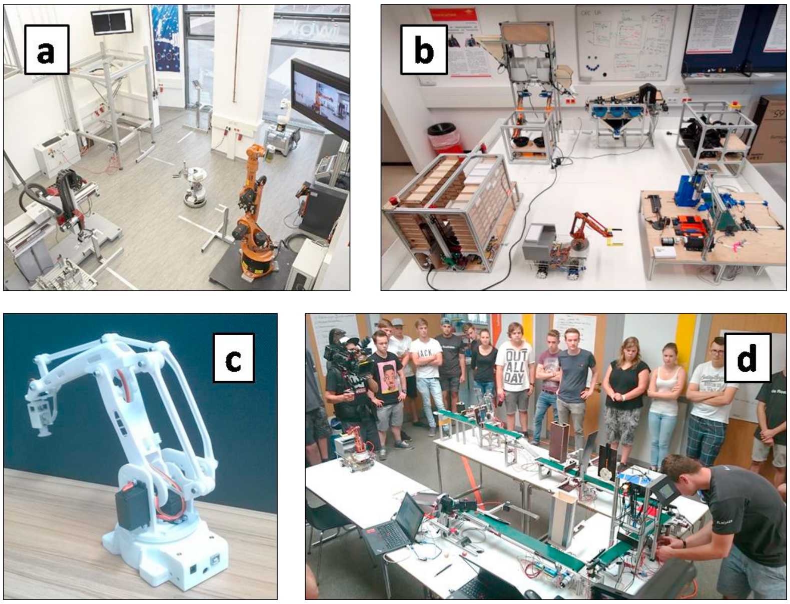

Fig. 2. (a) “Industrial” Digital Factory; (b) “Mini-Factory”; (c) 3D-Printed Mini-Robot; (d) portable “Mini-Factory”.

Both learning factories are easily reconfigurable (cp. for the Mini-Factory Fig. 2(b) with mobile robots and Fig. 2(d) with conveyors). Of course, the complexity and the precision of the industrial robots are higher, compared to the miniaturized version. Yet, for educational purposes on bachelor-level, the experience from four years of teaching has given strong evidence that typical engineering student problems are similar for both physical factory instances. Further, the Mini-Factory turned out to be able to serve as a strong educational resource also on master level, when assigning adequate tasks, e.g., sensor fusion or the implementation of machine learning algorithms. The Mini-Factory is only limited in terms of some tasks, such as precise gripping, handling heavy weights and above all mechanical topics. The entire Digital Factory (industrial and miniature) has been modeled as a 3-dimensional model (see Fig. 3). Simulation software allows for the execution of operations within this virtual model of the Digital Factory. Thus, learners can virtually operate machines, control a robot, change its tools, or steer autonomous mobile robots in a virtual context. In particular, virtual reality techniques can be used for educational purposes, as well as for effective industrial performance optimization. A further application is the support of maintenance concepts, e.g., a defective technical component. Augmented reality provides additional information for the maintenance engineer, to correctly, cost efficiently and quickly, repair defects. Moreover, virtual engineering tools could serve for many further purposes by enriching a given equipment scenario with additional technical data, detailed process condition data or even architectural or layout-data for the case of a physical production device. This requires a mobile device (e.g., tablet, mobile phone, virtual reality glasses). An identifier allows to accurately trigger virtual reality software visualizing corresponding data.

The UAS TW Digital Factory is equipped with multiple hardware and software to demonstrate the variety of technical options to practitioners and learners. Altogether, the different digital factory types can be applied for both, research and education. Teaching concepts and learning tasks might be designed theory-driven, within industrial prototyping or based on research results. Subsequently, the achieved educational settings can be implemented in both instances – industrial and miniaturized factory (except tasks that cannot be easily scaled down for usage on small and less precise machinery, and hence are applied in the industrial factory exclusively).

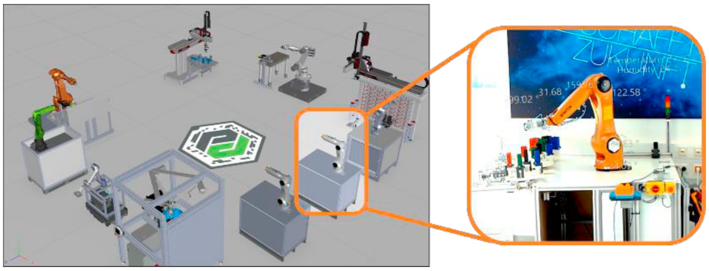

Fig. 3. Virtual Engineering in Robotics – the example of the Digital Factory at UAS Technikum Wien.

3. Two educational use cases in the Digital Factory: machine learning and virtual engineering

Both factories are used to carry out basic course exercises in robotics and mechatronics and for bachelor and master projects. Whereas the industrial factory also serves for industrial robotic applications (robot operation, kinematics, autonomous robots), the miniaturized factory is applied in workshops and for seminar groups with a high amount of participants. The virtual model and its applications can be used independently of time and location. In this regard, it is the most flexible learning resource. However, teaching experiences from the last two years have shown that virtual learning resources despite their vivid visualization and animation capabilities neglect certain effects that have to be handled in reality: for instance, within a virtual model, the components of a robot system move or change their status without physical reaction delay; similarly, all drives, wheels etc. are assumed to be 100% equal in the virtual model (unless one takes the effort to implement such reality effects by modeling and programming them with immense effort and questionable feasibility). Moreover, other than virtual devices, physical devices often have to be set-up physically (e.g., camera calibration). Thus real-world applications require different strategies. Summarizing, virtual engineering is a valuable tool in education as well as in practice but should replace physical experiments only partially.

3.1. Learning algorithms in robotics

Previously, robots were operated by means of fixed programs without any needs to react according to changing signals from the environment using sensor data processing. Currently, new applications in smart manufacturing are increasingly applying context-dependent control algorithms that are able to adapt for instance to differing objects to be gripped – depending on the location and the pose or other characteristics of the object [1,7]. Another exemplary application is any autonomous behavior of mechatronic systems, for example, autonomous driving (mobile robotics) or the execution of collaborative tasks together with humans (industrial robotics, service robotics) [8,9,10]. Typically, adaptive or learning behavior is implemented by means of machine learning methods applied to sensor data, e.g., a camera. For example, a robot could generate multiple pictures of an object to be grasped. For this purpose, a neural network would be trained with annotated pictures that correctly indicate the object and its pose to the robot system. The intention is to reduce manual and post-processing efforts to a minimum for object detection as well as for pose estimation. The described use case represents a typical setting [11,12,13,14,15] that has remained unsolved in many areas in the industry in terms of full automation: handling of materials and goods in warehouses, stores, etc. This use case requires an industrial robot, as object detection and grabbing accuracy require preciseness and identically repeatable robot movements. Further, the miniaturized robots are not able to carry the necessary workloads of objects to be detected and handled. The case can be used for educational content concerned with grasping approaches. Learning objectives in a robotics course could be for example to understand, explain and differentiate analytical from data-driven grasping methods, depending on a setting with well-known and less-known or even unknown objects.

Another learning objective could be the understanding of pose estimation methods (e.g., template-based, feature-based, voting-based, or learning-based) [16]. Also, topics with regard to deep learning and data-driven grasp-analysis [17,18] or learning content in the field of training data classification [19] could be supported by respective educational settings. Fig. 4 visualizes the setting of the aforementioned use case, as it was developed in the course of a master project in the Digital Factory of UAS Technikum Wien.

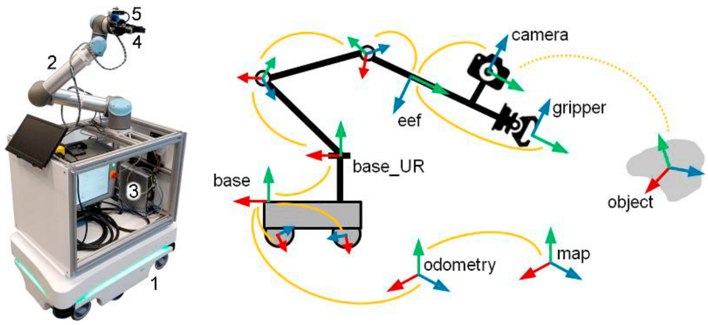

Fig. 4. Use case example: adaptive mobile manipulator including frames and kinematic structure.

The next steps to be conducted for this use case is the gaining of teaching experience with the developed learning materials, in particular videos, instructional texts, reflecting questions and further lab exercises.

3.2. Virtual engineering

Virtual reality (VR) and augmented reality (AR) applications are known for long [20,21]. Thus, they have been transferred into practical use due to the availability of powerful IT in the course of numerous industrial applications. Virtual engineering practices intend to apply engineering principles and to herewith use specific software when developing, testing or optimizing a product or a machine. Respective entrepreneurial goals are shortened system development cycles, reduced cost, risk and failure rates, as well as enhanced flexibility and adaptability. Hence, virtual engineering and virtual manufacturing seek to improve the design, the development and the systematic optimization of e.g., high-tech products or manufacturing devices, e.g., industrial robots, CNC-machines or transportation systems [6]. The application of virtual engineering is important in volatile environments that require agile procedures and rapid prototyping approaches [22]. Techniques such as virtual, augmented or mixed reality are also of great importance for teaching: If, for example, real-existing physical experiments could become dangerous for the learners or if the number of learners exceeds the laboratory capacity of a university, virtual engineering tools are a target-oriented supplement to teaching in the laboratory. A further application scenario of virtual techniques concerns the preparation and follow-up of the subject matter by students: on the one hand, this requires a theory-based examination of relevant textbooks and research articles. On the other hand, VR- and AR- use cases can significantly improve the vividness of what has been learned, for example by allowing the students to view the effect of their control commands on the movement of a robot immediately as animation in the course of the virtual robot operation. This can be done without any potential danger from incorrect operation of heavy and fast industrial robots. In addition, it can be repeated as often as required, at any time and from any location, independent of the teaching resources of the teaching institute. The learners can adapt the time sequence individually to their learning speed, can interrupt at any time, can repeat difficult passages and can explore particularly interesting constellations.

Today, digital VR- and AR-tools are broadly in use, in practical application as well as for educational purposes. Especially, simulation tools are in use that allow virtualizing most steps of the engineering approach. Also, maintenance operations can be supported by means of providing additional information for any object of the real world (e.g., through providing technical details for an installed device in the course of preventive maintenance or condition-based monitoring concepts). This relies on two basic principles: at first, the integrated virtual modeling of objects and their parameters and at second, the ability to flexibly analyze different views of the respective device [23], based on a shared data model that incorporates CAD parameters and system features. Here, education faces a severe challenge, as respective models are effortful in terms of development needs and have to be carefully inspected for reliability, validity and usability from a learner's perspective when intending to provide effective educational resources and scenarios. For example, virtualized devices can be designed and tested virtually with regard to motion behavior, collision issues, vibration analysis [24]. However, not only modeling but as well the software usage is time consuming and requires skilled staff. Despite high development effort, the huge advantage of virtual resources is their ubiquitous applicability for learning topics and teaching settings of nearly all kinds.

4. Conclusion

As UAS TW actually develops enhanced elearning capabilities, especially virtual engineering strongly contributes to teaching. During class, students explore how even elaborate models differ from real system behaviour. E.g., real robot drives never rotate identically. In the digital model, such variances have to be modelled if a high deviation of simulated results is observed. In a long-term perspective, further empiric research should be done to determine whether the educational benefit versus the required effort. On the one hand our virtual models have enabled the virtual access of students from international partner universities in principle. On the other hand, the observation of the mentioned deviations offers important learning for future engineers. As there are more examples for the mutual interdependencies of physical and virtual labs, we recommend systematic empiric research regarding the question, how these phenomena could be classified and transferred into substantial academic teaching practice.

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