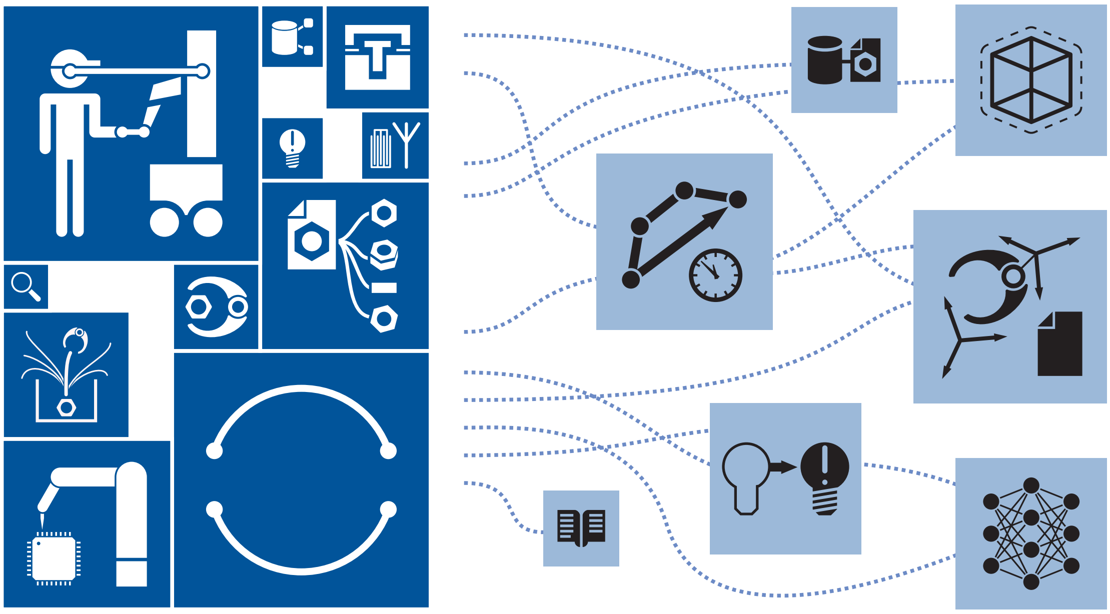

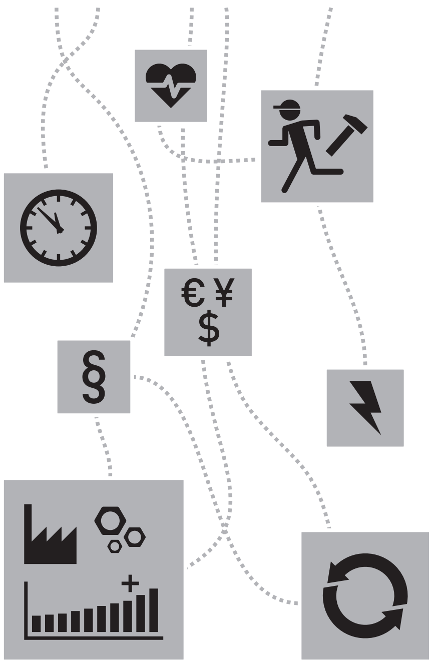

SMART ROBOTICS AT EMI

Challenges
Competencies
Solutions

HUN REN | SZTAKI
Hungarian Research Network
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Abstract

Research of autonomous manufacturing systems is motivated both by the new technical possibilities of cyber-physical systems and by the practical needs of the industry. Autonomous operation in semi-structured industrial environments can now be supported by advanced sensor technologies, digital twins, artificial intelligence and novel communication techniques. These enable real-time monitoring of production processes, situation recognition and prediction, automated and adaptive (re)planning, teamwork and performance improvement by learning. The paper summarizes the main requirements towards autonomous industrial robotics and suggests a generic workflow for realizing such systems. Application case studies will be presented from recent practice at HUN-REN SZTAKI in a broad range of domains such as assembly, welding, grinding, picking and placing, and machining. The various solutions have in common that they use a generic digital twin concept as their core. After making general recommendations for realizing autonomous robotic solutions in the industry, open issues for future research will be discussed.

1 Introduction

Automation and *robotics* have profoundly changed the character of industrial production as they brought about efficiency, predictability and consistent quality on a scale and breadth never seen before. However, these benefits came at a cost. Mastering uncertainty in automation is, namely, expensive—if possible at all—and both engineering common sense and production economy favor the removal of various factors of potential uncertainty from production processes right away. However, the rigidity inherent to this practice is becoming increasingly burdensome in many industrial environments. Moving towards high-mix/low-volume production [23], the sheer number and frequency of product variations preclude complete pre-production testing of resources and processes, and make repeated readjustment of production systems a chore. The mounting requirements of a circular economy—most significantly re- and de-manufacturing of poorly documented legacy products—add further unknowns to an already challenging complexity [77].

Long before technology and market expectations made automated solutions rigid and/or expensive, *humans* were recognized as the most flexible integrator of complex manufacturing systems [26]. Nowadays, combining the strengths of robots and humans in the same production setting is becoming either a necessity (e.g., due to the complexity or diversity of tasks being beyond machine-tractable), or an anticipated advantage (e.g., improving resource efficiency by wider process tolerances tackled through human ingenuity integrated into the system) [9]. At the same time, inclusion of humans in automated production is becoming reality as technological and scientific advances bring the compensation of disadvantageous human traits (higher error rate, limited rationality, lower predictability, physical and mental workload constraints) within reach, and makes the physical involvement of humans in robotized processes sufficiently safe [79, 78]. *Human–robot collaboration* (HRC), and in a more general setting, human–robot *teamwork*, can combine the strengths of robots and humans in the same production environment. Finally, the development of robotics is also driven by *labor shortage* in the manufacturing sector, and the need to compensate for the deficit in manpower by improving workforce skills and/or productivity.

As it was recognized about a decade ago, advanced robotics can respond to the challenges of productivity, flexibility, and the lack of human skills and capacity. With the development of robots and supporting technologies—in particular, artificial intelligence (AI)—next-generation robots could work, act and move autonomously in their environment. Autonomous robots could also operate in semi-structured industrial work environments, where there are basic rules, policies, and procedures in place, but they are not overly rigid. The general goals of activities are known, but the actors may have the freedom to decide how to achieve them. Here, robots are free from the physical boundaries that have surrounded traditional industrial robots mostly for the sake of human safety [53]. Indeed, the answer to the above challenges lies in *industrial autonomous robotics*, which refers to the field of robotics where machines are designed to perform manufacturing, logistics, and other operational tasks independently, using sensors, actuators, and AI-based decision algorithms to navigate and interact with their environment, not relying on human intervention. At the same time, their operating environment may contain other autonomous machines as well as human workers.

Autonomous industrial robotic systems are prime instances of *cyber-physical production systems*, since (1) they operate with a digital twin, (2) mostly in smart interaction with human operators, and (3) in close collaboration with other robotic and human agents [58]. No wonder that the digital transformation of the industry—which typically runs as the Industry 4.0 initiative (originally in Germany and thereafter also in Europe in general), or under the umbrella of the Industrial Internet Consortium (in the US) or Made in China 2025—was introduced in Japan as the *Robot Revolution Initiative*, re-branded recently as the *Robot Revolution and Industrial IoT Initiative*[1].

This paper summarizes, and to some extent generalizes, the recent results of industrial robotics research carried out in the Engineering and Management Intelligence Laboratory (EMI) of the Institute for Computer Science and Control (SZTAKI), belonging now to the Hungarian Research Network (HUN-REN). These works were motivated to extend our understanding of autonomous industrial robotics, to develop and generalize new models and solution technologies, and to apply them in various fields of industrial automation such as mechanical assembly, machine serving and smart machining, robotic inspection, robotic laser welding and grinding (see Ch. 4).

Certainly, there already existed classical solutions for all these applications, but they proved unable to fully meet the requirements of autonomous operation. In order

[1]https://www.jmfrri.gr.jp/english/

to deliver autonomous robotics applications, we considered it necessary to develop solutions that enable real-time robot localization, include sensor information into the feedback loop and utilize sequence and operation planning with the digital twin of the robotic cell, which is embedded into its recognized semi-structured environment. In the past decade, we have developed and generalized a set of enabling technologies to support the realization of various autonomous robotics applications. In the meantime we have been participating also in the development of a "toolkit" for collaborative robotics in manufacturing [69].

In what follows, we briefly summarize the requirements towards autonomous robotics, give a classification of its main categories, and suggest a generic system design framework for realizing such systems (see Ch. 2). Here, five stages of developing autonomous industrial robotic systems will be detailed, namely (1) designing, building and validating system configuration, (2) planning behavior and controlling execution, (3) interacting with the environment, (4) interacting with other autonomous entities, and (5) learning from experience. Next, the set of generalized enabling technologies will be presented (Ch. 3). In Ch. 4 some successful recent applications of the generic approach will be demonstrated through solutions developed by SZTAKI in collaboration with various industrial partners. These will encompass tasks that need to be fully automated without human intervention (picking and placing, laser welding, grinding, machining), tasks that require human intervention (inspection), or problems that require high-level human–robot collaboration (assembly). Finally, the concluding chapter identifies current research issues that go beyond technology, such as trust and responsibility in autonomous robotics.

2 A conceptual framework for autonomous industrial robotics

This chapter presents the outlines of a framework for developing autonomous robotic solutions we could define after conducting research and generalizing the lessons learned from a number of applications developed in different industrial domains. The emphasis is on *industrial* motivation, because working in such environments comes with rich and well-articulated background knowledge, constraints and task specifications, and rigorous, even standardized, rules for working with people (who are, against all regulations, the most severe sources of uncertainty) [5]. Therefore, we consider the environment *semi-structured*, where the possibilities for autonomous operation are limited by the above factors, but pose additional requirements.

2.1 Motivations

In industrial autonomous robotic systems, robots are replacing and/or operating with humans in fulfilling various roles of production and internal logistics [14, 31]. The motivations are manifold:

- There are tasks which *do not fit* humans, either because they are harmful to human physical or mental health in the long run (e.g., free-form grinding, monotonous picking and placing), or the technological conditions preclude human presence (like remote laser welding).
- There are tasks which can be *completed by machines better*—more precisely, more efficiently—than humans, such as welding, or most intra-logistics transportation tasks.
- In certain domains, human expertise and/or capabilities and capacities are *diminishing*, such as in inspection, or in near-net-shape manufacturing. Here, only

autonomous robotics can provide the missing skills, competence and resources.

- Finally, in some domains, efficiency is increased by humans and robots *working together*, as in mechanical (dis-)assembly, or more recently, in re-manufacturing.

In any of the above cases, autonomous robotic systems in production [63] face specific challenges:

- Such systems will be operating under conditions which are not fully predictable at design time.
- Autonomous robotic systems typically work in dynamic environments, consequently, their normal way of operation is adaptation to ever-changing conditions.
- They need the ability of deciding and acting under time pressure, in some settings and scenarios—especially when human safety requires it—even in real time. In any case, a so-called *anytime responsiveness* is an essential requirement in industrial settings.
- Such systems must warrant feasible, close-to-optimal operation in terms of "classical" key performance indicators (KPIs) of production, such as cycle time, error rate, service level.
- Autonomous robots must be able to work in rich interaction scenarios with humans.
- When working in collaboration with people in a shared workspace, human safety must be warranted. There is a number of ways to achieve safety in human–robot interaction, such as safety by control, motion planning, prediction, consideration of psychological factors, or a combination of these [50]. Note that even automation posed serious challenges to warranting human safety [52], while reconciling safety and autonomy may prove a contradiction forever [24].
- In particular, with the proliferation of AI technologies, new expectations emerged regarding trustworthy [46] and even ethical behavior of autonomous robotic systems [57].
- Finally, a capability of improving performance by learning is essential, on all levels of skills, individual agents and teams. In addition, using learning by demonstration, it is possible to reduce ramp-up time and enable domain experts to teach a robotic system with little to no effort.

2.2 Categories of autonomous industrial robotics

Driven by the often complex mix of the above motivations, in approximately the last two decades, various forms of autonomous robotics have evolved in industrial settings [21]. Based on the essential ways of how robots relate to human capabilities and humans, one can distinguish three main categories:

1. ***Relieve and delegate***: Here, autonomous robots take over some specific human functions. It is the allocation of human(-only) and robot(-only) resources on the task level, and it mostly means that humans and robots work separately also on tasks that will possibly be combined to a larger-scale outcome later on.

2. ***Augment and extend***: This category covers a productive combination of capabilities (both human and machine), but it is meant to remain mostly on the capability level, with minimal transaction logic across agent boundaries. This corresponds most to the one-on-one interaction cases which are in the focus of the majority of today's human–robot collaboration considerations. This kind of robot autonomy increases the performance of some human functions whose direct contribution is needed in an industrial setting, either by making it more refined or robust (augment), or by extending its boundaries beyond human limits (extend, e.g., with exoskeleton, advanced sensors). Note that augmenting and extending (as opposed to imitating or mimicking) human intelligence and capabilities was also the main motivation behind the now classic rational agent paradigm of AI [67], and still motivates many contemporary initiatives, too [13]. Moreover, mimicking human activities other than social interaction was not mentioned in the 10 grand challenges for robotics either [81].

3. ***Include and integrate***: This kind of robot autonomy is needed when humans and robots work in a shared workspace, engaged in transactions and mutual dependencies. Essentially, this is teamwork in a multi-agent setting, which can be executed under many kinds of regimes of coordination, cooperation, and collaboration [42]. This category represents cases where transactional complexity, group dynamics, the "social dimension" make the key contribution to resulting functionality. Given that we still have numerous unsolved problems in one-on-one cases, this category is now rather an extrapolated future. Also, this form of more complex teamwork will be more relevant for project-based work (as is the case in

the construction industry), rather than for production organized in smaller production cells where the size of the cell, as well as the volume and complexity of tasks would rarely call for several autonomous agents.

The above three categories are organized by the key place of autonomy (and complexity) in the execution hierarchy, and they are expected to coexist even as various enabling technologies evolve. In particular, much research and development are still expected and needed for realizing human–robot teamwork in the third category.

2.3 Generic tasks of realizing autonomous robotic systems for the industry

We have defined the following generic tasks of creating autonomous robotic production systems:

1. ***Designing, building and validating system configuration***. This generic task refers to model and system building, as well as to the methods that fit the model to the real system (establishing thereby its digital twin).
2. ***Planning and optimizing behavior, controlling execution***. These generic tasks include task sequencing and motion planning, offline "zero" robot programming, dynamic re-planning, and adaptation.
3. ***Interacting with the environment***, which includes calibration, sensing, perception and situation recognition, as well as establishing physical contact, actuating, and grasping.
4. ***Interacting with other autonomous entities***, including other autonomous robots and humans. This generic task also covers the whole area of human–robot collaboration.
5. ***Performance improvement, learning***, which also includes monitoring and evaluating performance, learning from experience, from successes and failures, and learning from interactions. Learning can be accompanied with life-cycle assessment, too, throughout each main stage (beginning, middle and end-of-life) of a robotic production system.

The above generic tasks are complex in themselves, and their successful execution needs interaction and iteration. The solution elements may vary from domain to domain, also depending on the actual application environment and its technical conditions. Despite all this variability, there still are some generic solution components which emerged from our autonomous robotic applications.

3 Generic enabling technologies

In order to achieve our research objectives, a number of components had to be developed and integrated in response to the challenges posed by autonomous robotic systems. The most important generic *enabling technologies and methodologies* we have developed so far are the following:

- linkage mechanism-based digital twin model,
- fitting of models to reality with prescribed tolerance,
- perception, measurement and calibration, including advanced image/point cloud processing,
- sequencing, planning, optimization,
- real-time control and visual servo, and
- supporting HRC by multi-modal human–machine interfaces

In the remainder of the chapter, we present our approaches to the enabling technologies listed above, along with references to key publications dealing with the solutions and their wider context in more detail. Due to the breadth and variety of underlying domains covered by the technologies and corresponding publications, a detailed review of each particular problem domain and assessment of our contribution would be far beyond the scope and dimension of this paper. Therefore, the reader is encouraged to consult our publication cited on the given topic, where a more thorough domain review and discussion of our solution are readily available in due depth.

3.1 Linkage mechanism-based Digital Twin —the core model

The core of our development methodology is a specific Digital Twin (DT) concept [49, 33]. In general, a DT is an organized digital model of some engineered system (such as a product or production system), which captures its function, structure, as well as its behavior and operation. A DT is, however, more than a (set of) model(s) because it is mapped with the physical system from time to time [60]. This continuous mapping produces a digital thread, i.e., data generated and collected during use or operation along the whole life-cycle of the system. Indeed, a DT is a "living" entity which changes together with the physical system, thereby establishing a digital representation of the physical system—with sufficient fidelity regarding structure, parameters and state—through time.

In our case, the DT is the digital representation of a complete robotic scenario, which can be utilized throughout the lifecycle of the corresponding robotic workcell. The DT not only represents life-cycle phases from design to commissioning, but is also applicable in a similar fashion in later phases, e.g., in case of reconfiguration, adjustment, or accidental misalignment occurring in the workcell. The general purpose of the proposed methodology is to facilitate the development steps and provide a systematic workflow for realizing different robotic tasks. Correspondingly, the underlying DT needs to be able to support a variety of scenarios. During the development process, the main purpose of the DT is to allow preparing/presetting *offline* (prior to execution time) and *online* (at execution time) planner tools in advance, thereby reducing necessary online, case-specific work (such as online programming or development of online planner tools). Furthermore, the DT needs to provide modification and calibration capabilities for the digital model. Consequently, it contains a number of models, which enable offline and online planning, simulation and preparation. As the DT needs to support continuous improvement and refinement without losing earlier preparation results, the model definitions need to be parametric and updatable. By using parametric representation, planning or evaluation steps can easily be recalculated by changing the input parameters.

The DT of our robotic applications is modeled with *LinkageDesigner*, a parameterized mechanism modeling tool for virtual prototyping of *linkages*, i.e., systems of interconnected elements (links) subject to kinematic constraints [15, 55]. *LinkageDesigner* is an add-in software package of *Wolfram Mathematica*[1]. It is designed to analyze,

[1]https://www.wolfram.com/products/applications/linkagedesigner/

synthesize and simulate linkages with open- or closed-chain structure, as well as a combination of both. Using the symbolic calculation capabilities of Mathematica, LinkageDesigner supports fully parameterized linkage definition and analysis, too.

One of the most important features of autonomous robotic applications is the robustness to uncertainties in the environment. In this framework, robustness is ensured by an integrated approach to planning, wherein knowledge of state estimation uncertainty and of task execution uncertainty both form an integral part of reasoning about the execution of a task.

Parametric mechanism modeling with relative joint coordinates is very efficient in terms of computational resources. In case of generic kinematic graphs, certain kinematic pairs must be modeled with non-redundant loop closing constraint equations. Generating these parametric constraint equations automatically is usually a challenging task. However, this prepares the ground for handling the differences between "as-designed" and "as-built" models and creating the kinematic digital twins [16] from these different models.

3.2 Striving for twin closeness—Model fitting to reality with tolerance

Robots operating in an unstructured environment must be able to sense and interpret their environment. We have provided a generic design methodology for the design of robotic cells operating in such environments, which can be used to guide the DT development of various robotic workcells, on the basis of *the kinematic digital twin*.

The generic kinematic graph-based calculus can be successfully employed in a wide range of different problem domains of manufacturing, such as robot motion planning, process planning, tolerance analysis, point cloud processing, layout planning and object localization. The crux of the solution is that parametrically generated kinematic graphs can be used for solving many different real-world design and planning optimization problems and they can be considered as the bridge between the design intent and measured reality.

Making models uncertainty-tolerant is, however, only one of the key challenges to tackle. In order to make offline planning and simulation results applicable to the physical system, the deviation between digital and physical workcell characteristics (geometry, behavior, etc.) needs to be within acceptable limits. In terms of geometry, this means that the digital and physical counterparts need to be within a feasible tol-

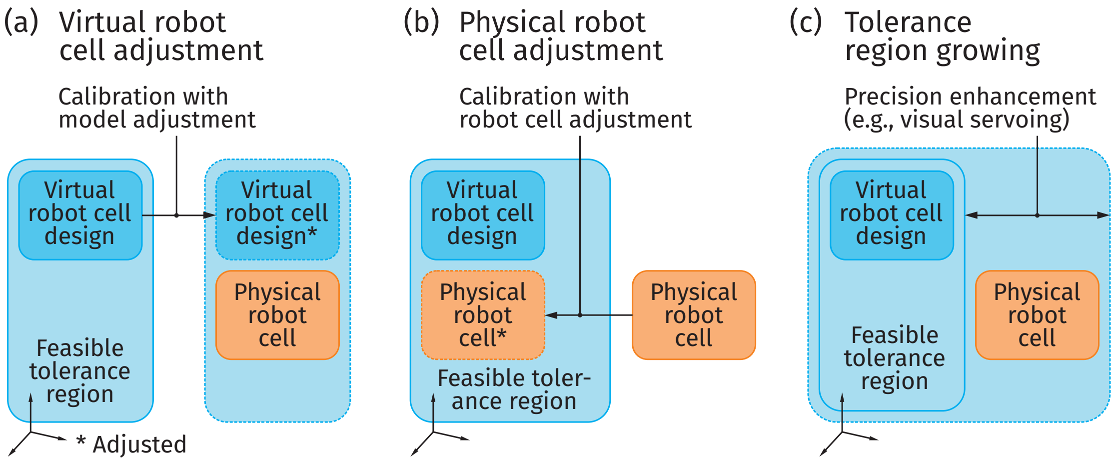

Figure 3.2.1. Digital twin closeness and deviation reducing methods, which include (a) calibration-based adjustment of the virtual workcell model, (b) that of the physical workcell, and (c) growing the tolerance region e.g., by servoing [73].

3.2

erance region (bound by application-specific feasibility criteria). To represent these characteristics, the term of digital twin closeness (in short: *twin closeness*) has been defined [73]. Twin closeness is based on a deviation function between the digital and physical system counterparts, defined on a geometric tolerance basis. The deviation function is determined by applied technology (e.g., robot control, metrology or end-effector type) and implemented artifacts (e.g., geometric features) of the workcell. This function includes the geometrical deviation of the objects in the cell, as well as the trajectories of the dynamic objects, such as the deviation between the designed and realized robot tool path. Twin closeness can be improved via DT calibration in general. This can be realized by parameter adjustment on the model side (see Fig. 3.2.1(a)), or by adjusting the physical workcell (see Fig. 3.2.1(b)). Additionally, the tolerance region can be widened by tolerance enhancing techniques (such as visual, tactile or force servo control of robots), equipment improvement (e.g., more precise metrology system or manipulator), or simple geometric features like chamfering (see Fig. 3.2.1(c)), through design specification or model modification.

Our proposed generic system design workflow is based on the methodology we have developed for the design of flexible robotic pick-and-place workcells using digital twins [73]. It was also applied when building up the DT of a robotic cell for free-form grinding [20] and five-axis machining. Recently, we have also defined a framework for managing the lifecycle of the kinematic digital twins [16].

3.3 Perception and object recognition

Real-time robotic digital information architectures are the gateway to analysis and performance in operational tasks [1]. While computational simulation offers an early surrogate data-source, our ability to capture the complexity of the real world remains limited. *Sensing* (as packaged into modular networked sensor subsystems) coupled with *action* (active-sensing paradigm) still remains the best lens into the traditionally opaque world [32]. However, ensuring provenance and quality of the raw spatial–temporal data streams from multiple spatially distributed and temporally asynchronously sampled sensors is critical. Core to the robot-supported active-introspection are sensor-suites mounted on individual robots or across the system, as these can produce a significant amount of spatial–temporal information about the world. Coupled with information-enhanced real-time/interactive mobility and manipulation, this empowers a range of advanced algorithms. All the challenges of Big Data (5 Vs: Velocity, Veracity, Variety, Volume and ultimately Value)[43] manifest as these robotic systems-of-systems act as sensitive instrumented probes to gather data to inform decision-making in application-verticals, from agriculture to infrastructure inspection [9].

Vision-based sensing methods (2D or 3D) are typically used for resolving uncertainties in the system. Uncertainties can be, on the one hand, environmental factors, such as a pose or location of another robot or a human as obstacles, or, on the other hand, process-related factors, such as the number, type, shape, pose or location of workpieces present. The necessary information is collected using the sensors present in the physical system, in form of images or point clouds, and then, after (conventional or data-driven) data processing, the relevant information can be uncovered and forwarded to the planner modules in the digital twin to adequately adapt the operation.

Difficult sensing problems in an unstructured environment can be tackled by *data-driven AI method*s, such as *deep learning* models [44]. However, one of the main obstacles to applying deep learning models to visual perception of the environment is the lack of domain-specific labeled training data. To this end, we have developed a *sim2real transfer learning* method based on domain randomization to automatically generate labeled synthetic datasets of typical objects in a robotic work environment for object detection, providing the training data of a convolutional neural network (e.g., YOLOv4 [6]). Our solution [28] is suitable for industrial use—an example of object detection using our solution is depicted in Fig. 3.3.1. Furthermore, we extended our method with orientation estimated [27]—an example is shown in Fig. 3.3.2.

We also developed a generic technology to automatically *calibrate* an articulated robot arm using measured *point cloud data*. The method captures the inner structure

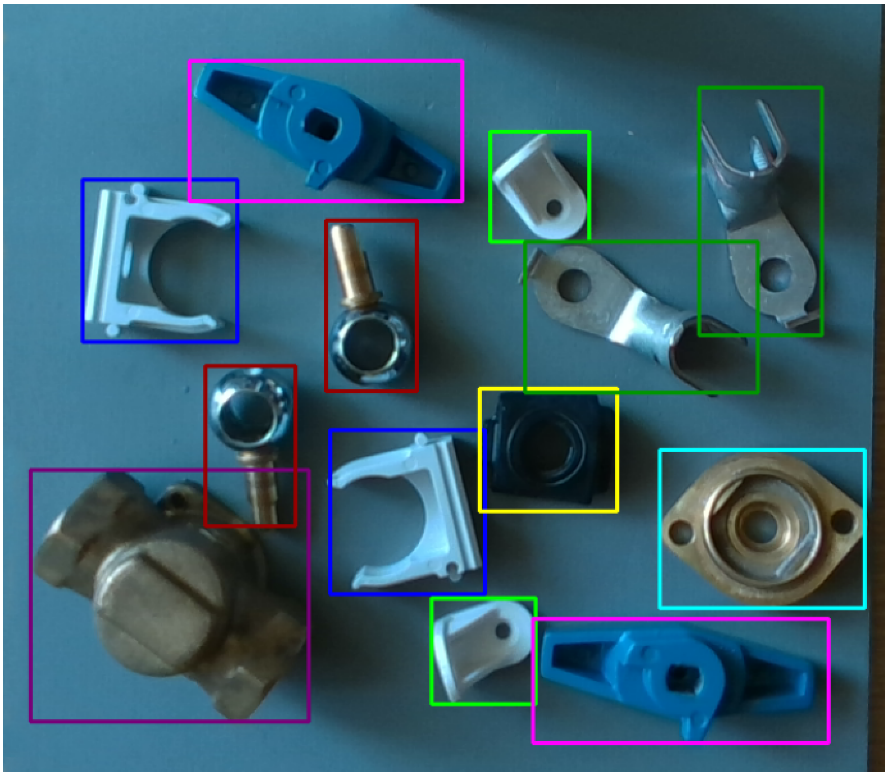

Figure 3.3.1. Qualitative evaluation of our sim2real domain randomization method for object detection [28].

of complex engineering objects from measured datasets. In the workflow developed, the point cloud is segmented first, then the CAD models of the objects in the workcell are recognized and fitted onto the segmented point cloud. To boost the computational efficiency of the method, parallelization was performed by applying general-purpose programming of the graphics processing unit [29].

*Real-time recognition algorithm*s should start from the available data format—in the case of a 3D scanning tool, this is a point-cloud-based tessellated geometry, typically in STL format. In order to understand and interpret this perceptual information, a real-time feature recognition algorithm should be developed, which is not readily available in the research community at this time. 2.5D machining feature calculation assuming an STL workpiece definition and a semi-finished product offers a set of capabilities that can be useful for this interpretation. In our recent work, we have used a graph-based representation of the triangulated object and utilized classical graph-based searching and clustering methods for calculating the relevant geometric features [16]. This method will be extended to implement a real-time algorithm, therefore, classical computational algorithms and convolution-network-based AI algorithms are also in the focus of development.

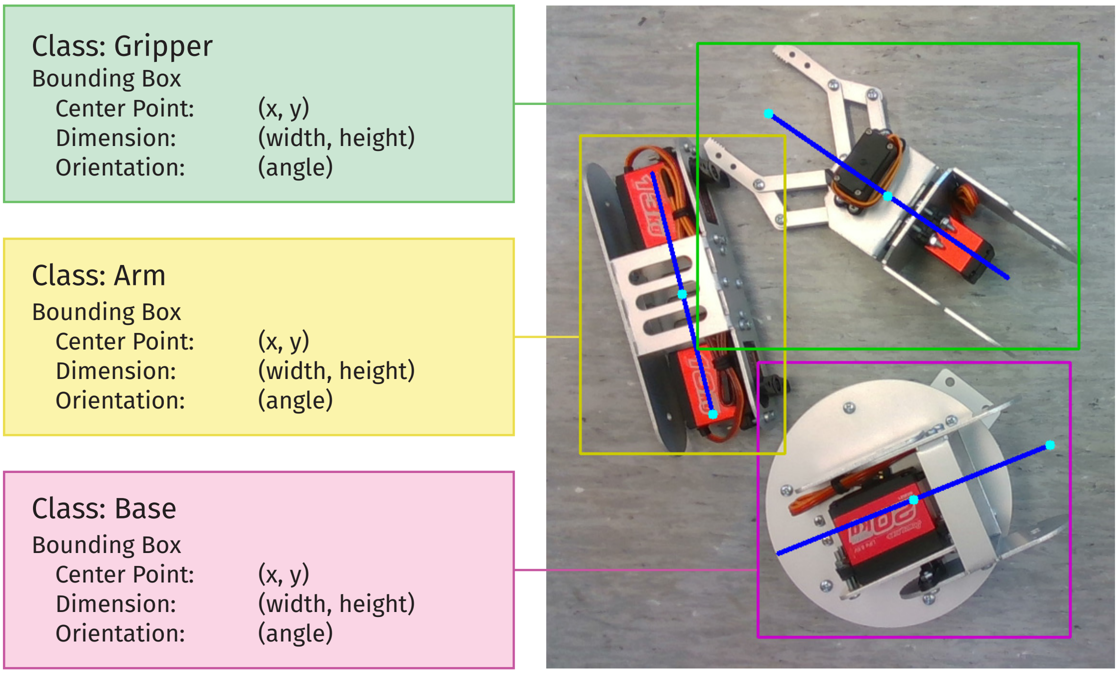

Figure 3.3.2. Qualitative evaluation of our sim2real domain randomization method for object detection enhanced with orientation estimation [27].

3.4 Process planning

Having a calibrated DT enables *automated process planning*[4, 83], even in real time if required by the particular application. In robotics, process planning is typically subdivided into *task planning* and *motion planning*[25]. The former is a combinatorial problem that involves the selection and the sequencing of the tasks to execute, as well as their assignment to resources in case of multi-robot systems. In contrast, collision-free motion planning is a problem of geometrical nature. The two problems are interrelated: while motion planning takes the results of task planning as input, accessibility issues due to a potentially mistaken task plan may only surface during motion planning. In such cases, the planner may have to reconsider task planning.

Obviously, the decisions to make, as well as the constraints and objectives to consider during task planning depend greatly on the particular application. Decisions may involve the *selection of a robot joint configuration* for each task, the grasping mode to apply, the direction of the motion, etc. This selection is closely coupled with *task sequencing*, often subject to precedence constraints. Finally, various cost functions can be used to evaluate the quality of a solution. Due to the complexity of the problem, previous approaches to robotic task planning use application-specific—typically, meta-heuristic—solution methods.

In order to avoid such redundancies, we have developed *ProSeqqo*, a generic solver for task planning in industrial robotics. It provides (1) a powerful representation language, and (2) advanced search techniques for modeling and solving process planning and sequencing problems [83]. Following the best traditions of theoretical research in AI planning, the problem can be defined using an intuitive, easy-to-comprehend and easy-to-edit *problem definition language*. This representation is hierarchical: there are (1) processes on the top level, (2) alternatives for the possible ways of executing a process, (3) series of elementary tasks for executing an alternative, (4) multiple candidate motions for performing each task, and (5) for each motion, the sequence of configurations the robot must visit (see Fig. 3.4.1). *Precedence constraints* can be defined between two processes or two motions. Along with the problem, a rich set of optimization criteria can be defined in terms of cost factors of using and changing resources, of making moves, or of penalties for violating some requirements. ProSeqqo transforms the declarative problem definition into a generalized traveling salesman problem (GTSP) formalism and applies a combination of mixed-integer programming and local search methods to solve it. For this purpose, it relies on the *vehicle routing problem* (VRP) library of Google OR-Tools, extended with custom algorithms. It was demonstrated that the proposed language can capture the overwhelming majority of the robotic task sequencing problems investigated earlier in the scientific literature. Moreover, the application of the modeling language and the solver was demonstrated on five, seemingly very different use-cases, including both real industrial applications and lab demonstrations [83]. Results of thorough computational experiments were also presented, showing that efficiency of ProSeqqo makes it amenable for online applications, too. ProSeqqo has been made available open-source for the scientific community[2].

An important direction for future research in the field of task planning is planning for robotic diagnosis: in this field, real-time planning must be interleaved with diagnostics, since future tasks depend on past diagnostic results [48].

Similarly, the most appropriate approach to motion planning depends on the particular application. If the robot operates in large open spaces, simple *point-to-point* motions can be suitable. In applications where collisions may occur, mostly between the workpiece and the robot end effector, or strict constraints apply to the relative position of the workpiece and the end effector, it is expedient to compute the robot motion plan in the Cartesian *task space*. In contrast, if collision detection must ac-

[2]https://github.com/SZTAKI-hu/proseqqo

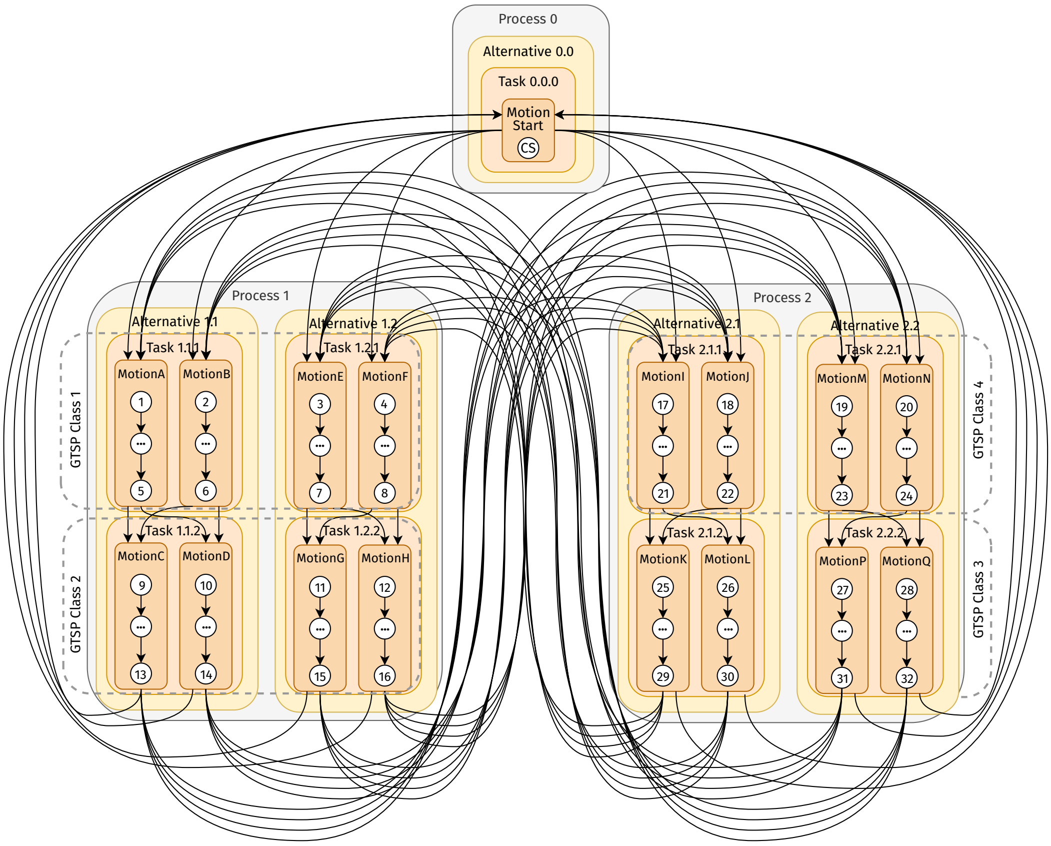

Figure 3.4.1. GTSP representation of a sequencing problem with two processes, two alternatives per process, and two tasks per alternative [83].

count for all moving objects in the workcell, including the end effector, the workpiece, as well as the robot links, planning in the robot joint configuration space cannot be avoided. In such cases, the greatest challenge becomes tackling the high-dimensional state space (typically, 6- or 7-dimensional, depending on the robot kinematics), which requires the application of sampling-based path planners, such as the single-query Rapidly-exploring Random Tree (RRT) [51] or the multi-query Probabilistic Roadmap (PRM) [39] algorithms. Again, to have a generic but fully customizable solution, we developed our own library of collision detection and motion planning algorithms for articulated industrial robots [82]. A special feature of the library is the support of so-called conservative advancement methods to guarantee that the computed motion is free of any collisions throughout the *continuous motion* of the robot. This is a considerable advantage compared to classical approaches that perform collision detection only at some discrete, sampled points along the robot path. An open challenge in the field is integrated task and motion planning for industrial robots [47].

3.5 Visual servo

Robotic tasks, where sufficient twin closeness (see Sect. 3.2) cannot be achieved by offline calibration methods—e.g., fixtureless, robotic part feeding with strict placing tolerances—require *tolerance growing* techniques such as visual or force servo-based robot control. *Visual servoing* techniques [10] provide a way to achieve accurate positioning even if the accumulated geometric errors in the system would not allow the positioning with the required precision. Accumulation of errors in robot, workpiece, workspace and tool manufacturing, as well as errors in assembly and control and errors in imaging and image processing can result in deviations in the range of millimeters, which can render conventional application infeasible, even where moderate (sub-millimeter) precision is required.

Consequently, the visual servo system can be applied by defining the target point as the fulfillment of a measurement-based condition instead of using exact geometric coordinates. We use a sensor-coupled, direction-selective, visual servo-based, robotic micro-positioning system [74, 75], in which the reference feature—corresponding to the tool—and the target feature—corresponding to the workpiece—are identified using eye-in-hand cameras in a robotic inspection scenario (see Fig. 3.5.1).

Using the distance between the reference feature and the target feature, which is determined based on the processed camera images, a motion command is issued to the robot controller to iteratively reduce the distance below a target threshold (corresponding to the required precision). The detection and localization of the aforementioned features can be realized using various image processing algorithms. In order to achieve fast and robust operation, our patented solution applies a deep convolutional neural network for image processing [17].

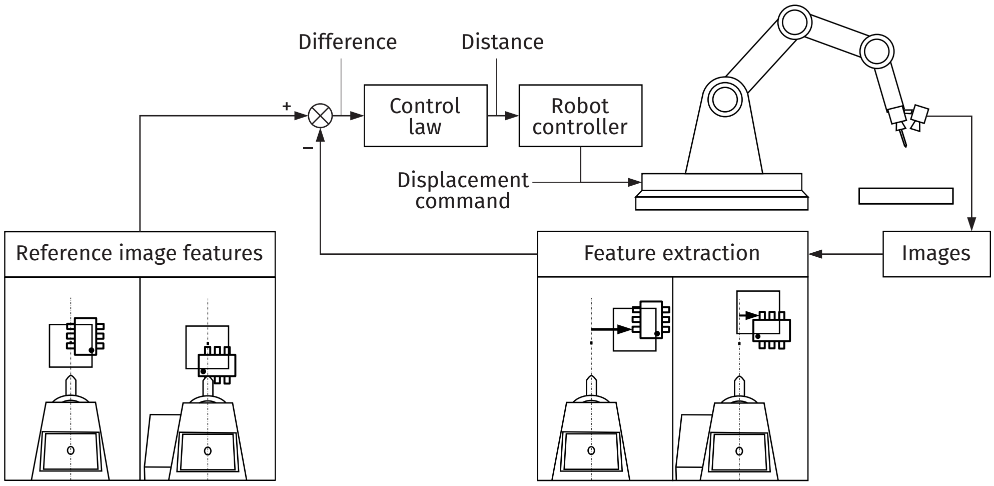

Figure 3.5.1. Concept of the visual servo control for our inspection scenario.

3.6 Supporting human–robot teamwork

With recent scientific and technological achievements, the evolution of a meaningful and productive symbiosis of robotic and human resources in production is within sight [78]. As humans and robots work side by side, the feasible forms and supporting technologies of human–robot collaboration will diversify. Now, it is already worthwhile to think of a *continuous spectrum* of human/robot involvement in production, ranging from the human-only to the machine-only end. Also, a variety of co-action and organization forms appeared already. These exhibit various degrees of autonomy of the humans and robots participating in the process, ranging from cooperation with discrete coupling points of human-only and robot-only processes, over collaboration with simultaneous, continuously coupled robot and human involvement, to coordination of multiple humans and robots. In order to facilitate human–robot teamwork in manufacturing, we have (1) defined a generic multi-agent framework, (2) developed a manufacturing execution system which supports multi-agent activity, and (3) a multimodal bi-directional human-machine interface controller system. These will be presented in the sequel.

3.6.1 Multi-agent approach to human–robot teamwork

As the diversification and evolution of human–robot interrelations advances in industrial production, it is expected to be of growing importance that individual robots, humans and their modes of operation fit seamlessly into a “big picture” that allows consistent and comprehensive assessment, planning and task execution, even in a conglomerate of components with variable capabilities[64]. Humans are certain to enter the production scene with different preliminaries and varying mindset, while machine components and their computing backgrounds will likely come from a wide variety of vendors.

In such multi-player settings, it is crucial to maintain good interoperability, as already recognized and pursued elsewhere in the practice of cyber-physical production systems. In human–robot collaboration, however, such a consolidation still lies ahead, as the rapidly evolving domain is still far from establishing common ground regarding fundamental concepts and perspectives. In order to contribute with a "baseline" orientation primarily in the context of industrial production, SZTAKI has proposed a framework combining and extending concepts from the domain of *multi-agent systems* [42]. The scheme considers three interlinked levels of organization, namely (1) capabilities, (2) an individual agent, and (3) a team built on the interplay of individual agents (see Fig. 3.6.1). The hierarchy integrates existing classification concepts from the multi-agent domain, such as the SRK (skill–rule–knowledge) taxonomy in agent capabilities [66, 12], the BDI (belief–desire–intent) perspective [7, 65], concepts of autonomy levels in executive functioning of the individual agent [79, 59], as well as roles, transactional logic and belief/goal alignments in team cohesion.

Many frameworks of concepts in the multi-agent domain pursue a rather "closed" structure, either assuming the involvement of artificial (and thus limited and formalizable) agents only, or placing any interacting human (sometimes, not even specifically multiple humans) in their own separate partition of the entire scene [61], with access to the team of artificial agents granted through a unified human–machine interface only. Such approaches would be of limited utility in characterizing, designing or operating mixed human–machine teams of varying composition, role allocation and multiplicity [79, 80]. Therefore, we have opted for considering any human involved as one of the agents integrated into the multi-agent system, and aimed for an extended version of frequently used concepts to accommodate characteristics which currently are almost exclusively reserved for humans (e.g., *expertise* as a separate level in the capability stack, or mixed rational–intuitive approaches in agent behavior patterns). Given that the HRC domain—especially on the level of human–robot teams—is likely to undergo longer and profound evolution in foreseeable time, the conceptual framework is designed to remain open in order to facilitate future revisions.

Agent autonomy and closely related *leader–follower relationships* express how much of robot action is directly determined by human agents, and vice versa. In any case, an agent needs to take the responsibility and leadership when performing the

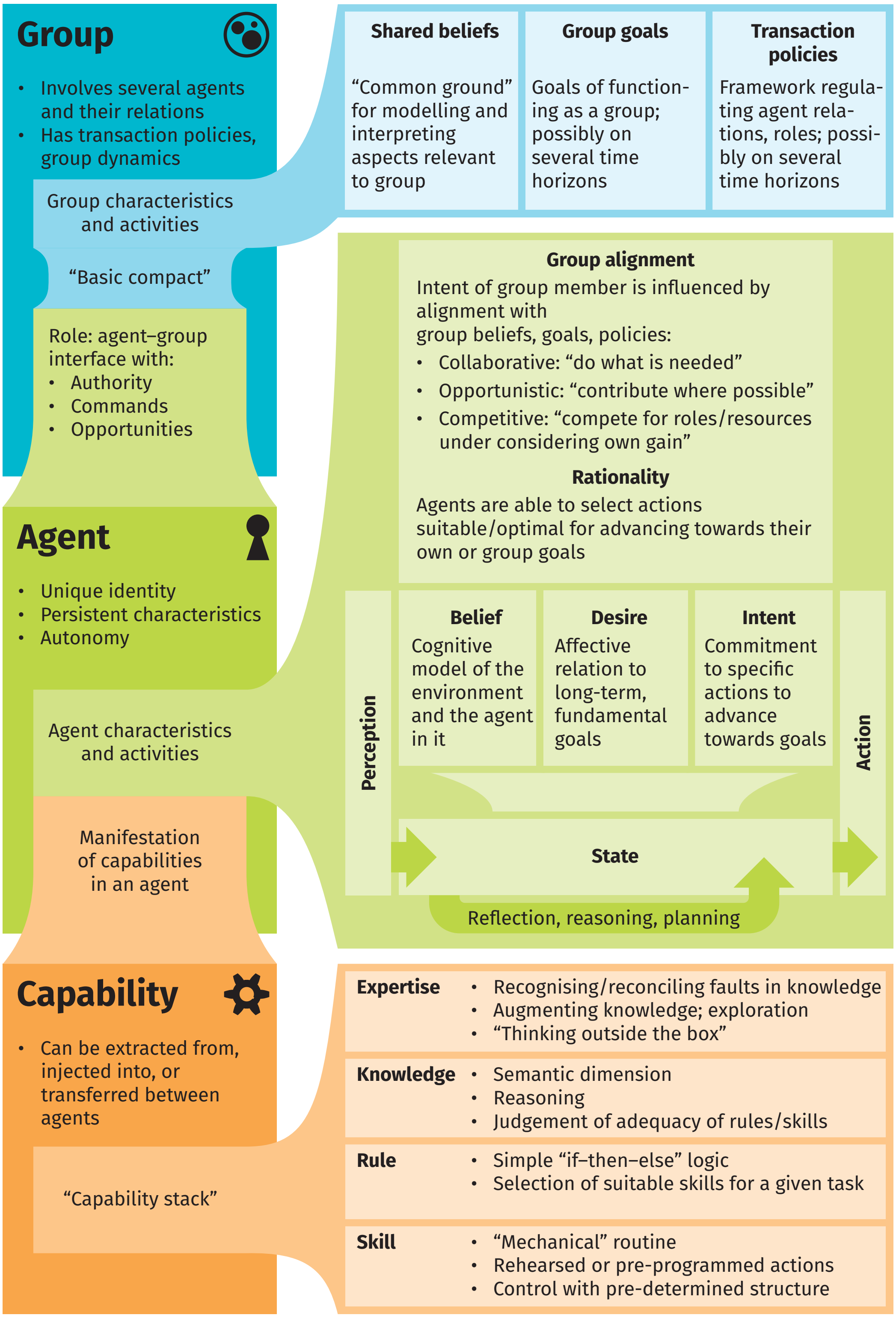

Figure 3.6.1. Our conceptual system for multi-agent human–robot teamwork [42].

3.6

given task. We have classified task execution scenarios along the autonomy of participating agents [79] (see also Fig. 3.6.2). During task execution, either the human or the robot may assume an active (leading) role, or only support it (as a follower, performing auxiliary actions on-demand, serving as a fixture, etc.) or behave inactively (not taking part in the task, merely being present as an obstacle). Adaptive robots and intuitive humans are able to re-assign leader/follower roles on-the-fly. With some few exceptions, recent research assumes that the roles are assigned before task execution. We also followed this practice when organizing HRC in mechanical assembly.

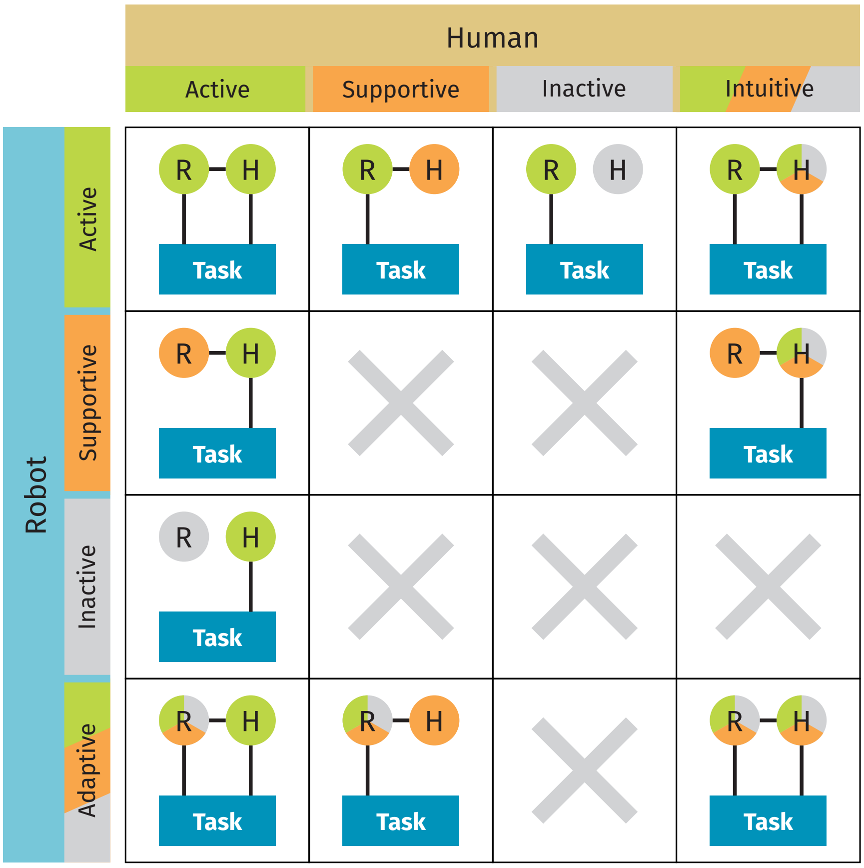

Figure 3.6.2. Possible combinations of the human and robotic workers' roles [79].

3.6.2 Manufacturing Execution System as a Service (MESS)

Digital transformation and artificial intelligence are creating an unprecedented opportunity for innovation across all levels of industry and are transforming the world of work by enabling factories to integrate cutting edge information technologies into their manufacturing processes. Manufacturing Execution Systems (MESs) are abandoning their traditional role as legacy execution middleware to embrace a much broader vision of functional interoperability enablers between autonomous, distributed and collaborative cyber-physical production systems. In line with this vision, we have developed a general methodology that enables the modeling, digitization, and integration of capabilities exhibited by a variety of *isolated* workcells into a *unified*, *standardized*, and *DT-augmented* manufacturing execution system as a service (MESS) [3]. The result is a cloud-based, reliable, reconfigurable, and interoperable manufacturing architecture, which privileges the Open Platform Communications Unified Architecture (OPC UA) and its rich possibilities for information modeling at a higher level of the common service interoperability, along with the Message Queuing Telemetry Transport (MQTT) lightweight protocols at lower levels of data exchange. The proposed MESS architecture (Fig. 3.6.3) has been applied in several use-cases involving autonomous robotics and logistics in our pilot manufacturing laboratory of excellence for industrial testbeds [41].

In order to realize the idea of generally embeddable I4.0-compliant CPS, a "minimalistic" CPS service model has been conceptualized. A CPS is basically expected to embody a set of core service concepts whose selection is necessary to guarantee: (1) a core *digital representation* of a CPS; (2) a *service interface* to the MESS collaborative environment; and (3) *compliance* with MES definition and I4.0 components in RAMI 4.0. A CPS can expose its capability in terms of (micro or macro) *services*, which can be invoked by means of parameterized *functions*. Invoking a function triggers the execution of its related *tasks*, necessary to track the advancement, thanks to an event-based *reporting* mechanism. CPS might also have operating parameters called *variables*, which can point to any exposed signal of the specific equipment and whose values can be utilized in the decision-making process of a production *routing*. Functions are organized and linked in routing by means of *precedence* edges, which represent the necessary *conditions* for a specific function to execute. The interface of a CPS basically permits to: (1) connect, disconnect, and refresh requests from the system core; (2) provide information on CPS structure; (3) enable the execution of its functions (services); (4) report on a service execution status and its inherent variables; and (5) provide error handling.

MESS is a set of integrated software and hardware components that provide functions for managing production activities, from job order launch to finished products. By the use of nearly real-time data, it initiates, guides, responds to, and reports on production activities as they occur, in compliance with MESA guidelines.

As illustrated by Fig. 3.6.4, MESS has been demonstrated in various production use-cases, utilizing a variety of elements: (1) single robot arms, (2) production assembly

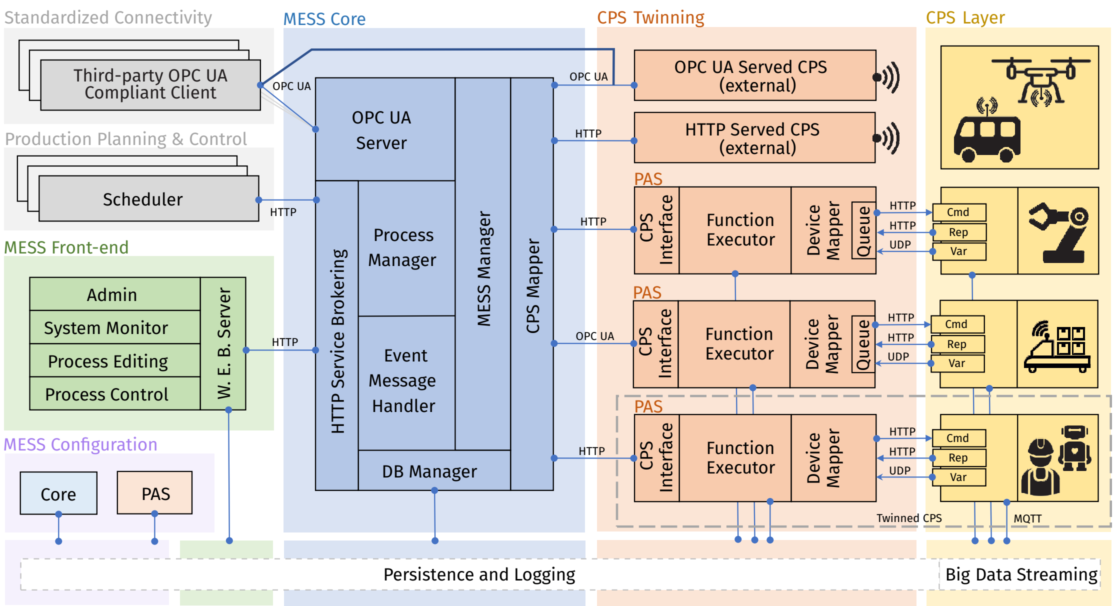

Figure 3.6.3. Overall picture of the MESS architecture.

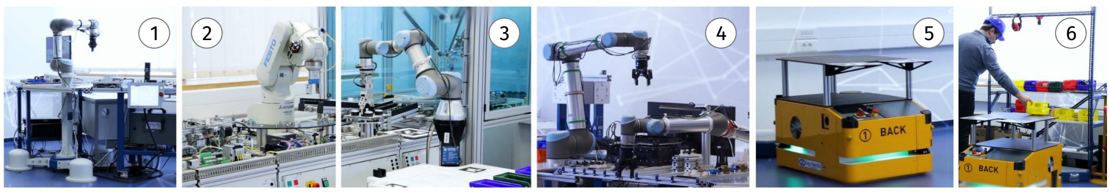

Figure 3.6.4. Physical devices of CPS in MESS demonstrated use-cases

line, (3) Autonomous Guided Vehicle (AGV) or Autonomous Mobile Robot (AMR) fleet, with (see 3) and without (see 5) robot arms, (4) collaborative robots, and (6) human-operated components, such as the warehouse and a digital work assistance system.

Some of the integrated cells—such as the assembly line [71], the human–robot collaborative workcells [40], and the AGV/AMR fleet [45]—are complex CPSs with their custom-tailored DT. MESS currently integrates CPSs from the *SmartFactory* developed at HUN-REN SZTAKI, the *New Knowledge Space* of the University of Győr, a CPS developed at the Department of Manufacturing Science and Engineering at BME, and, more recently, the *Innovation and Demonstration Space* at HUN-REN SZTAKI.

3.6.3 Communication via multi-modal human–machine interface

Human–machine interfaces in the manufacturing industry have been thoroughly explored for over a decade now, both from the perspective of efficient and robust information flow, and ergonomics aspects. In the latter regard, physical ergonomics (i.e., aspects of the work environment with direct physiological impact on humans involved) is more and more often extended by *cognitive ergonomics*, taking into account the individual optimal operating range of humans with respect to perception and associated cognitive processes [34]. Recent years have witnessed growing interest and new results in the cognitive ergonomics domain, combining new findings of cognitive sciences and technological advances in visualization, contactless sensing, wireless data transfer, and artificial intelligence solutions to transform the character of work environments and the ways they integrate human workforce into production processes.

Augmented Reality (AR) technologies combined with machine learning techniques have seen significant breakthroughs in recent years, enabling a shift in the way we approach complex scenarios such as human–robot collaboration training and worker instructions. Although novel approaches are constantly being tested in the industry, the introduction of AR solutions still lacks the necessary background research, especially in the field of human factors, to find the key exploitation strategy for the device. As advanced human–machine interfaces are best utilized in human–robot collaboration scenarios, which rely heavily on the availability and rapid processing of sensor data, an additional research domain arises in low-latency data transmission. Currently, reliable sensor connection solutions generally utilize wiring, however, its presence increases the complexity of path-planning problems, while wireless solutions are inherently more intuitive with mobile robots. Therefore, an opportunity presents itself with the recent emergence of *5G technology* that provides key low-latency wireless communication methods for robotics and advanced human–machine interfaces.

In the dynamic environment of human–robot collaboration, a key for boosting the efficiency of human workers is supporting them with context-dependent work instructions, delivered via communication modalities that suit the actual context. Workers, in turn, should be supported in controlling the robot or other components of the production system by using the most convenient modality, thus lifting the limitations of traditional interfaces as push buttons installed at fixed locations. We have developed a workflow for context-dependent multimodal communication in a collaborative human–robot work environment and implemented a *Human–Machine Interface Controller* (HMIC) system [35]. The system's overall architecture is presented in Fig. 3.6.5.

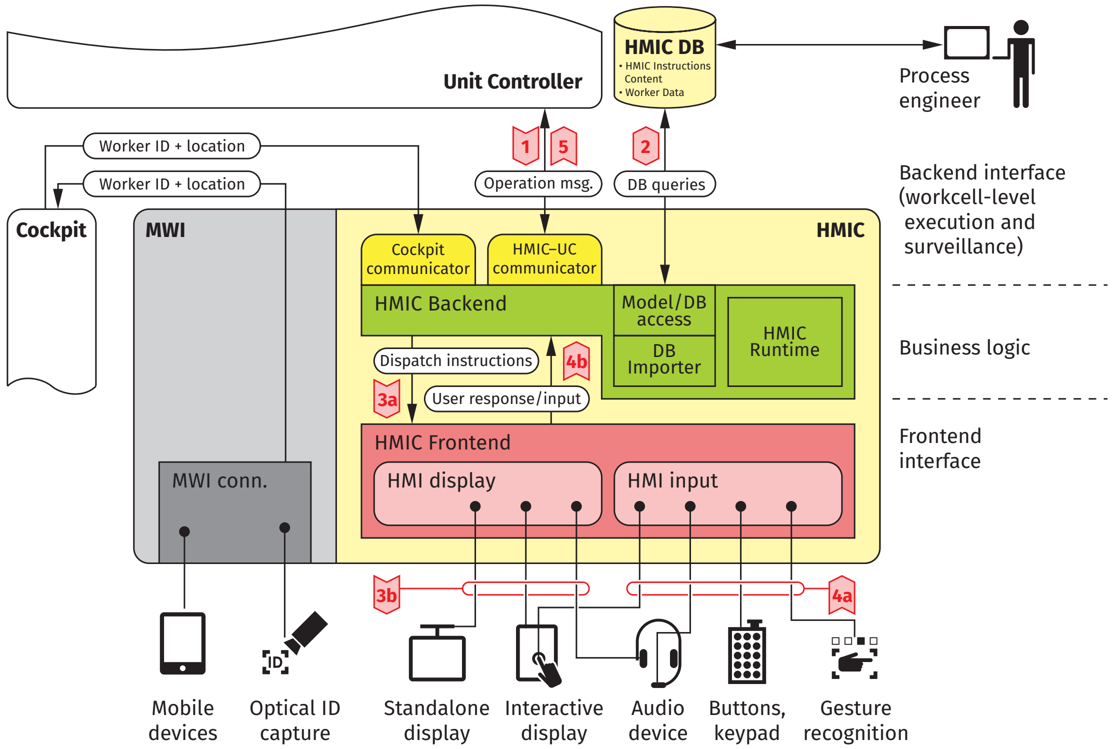

Figure 3.6.5. Architecture of the Human–Machine Interface Controller [35].

The HMIC system was first adapted in human–robot assembly to support the bi-directional, multi-modal exchange of information between a robotic and several human agents. Main contents of the communication, skill-level dependent work instructions for humans were generated by an assembly planner system, from assembly plans [36] (see Sect. 4.5).

HRC performance, and safety in particular, can also be improved by anticipating and avoiding potential collisions between the robot and human operators. For the mechanical assembly domain, where close human–robot interaction can easily lead to collisions, we have developed an early *warning system*. In contrast to traditional techniques which use acoustic or visual signals, we have applied a combination of Virtual Reality (VR) and depth camera-based visual processing to project future states of the workcell. When the distance between the robot and the human operator was within a tolerance range, vibration signals were sent to the human [62]. Being thus continuously informed about the prospective movement of the robot via VR, the human operator could adapt his/her movement to avoid collision. We are convinced that such transparency and predictability are keys to raising and maintaining trust in a team composed of robots and humans [57].

4 Autonomous industrial robotic applications

In this chapter, we present in a nutshell our recent autonomous robotics applications, which were developed and deployed using some of the above enabling technologies and methodologies. The applications are described here only briefly, but the given references provide links to detailed information about the technological background of each solution. As already expressed in Ch. 3, a comprehensive presentation of the specific domains of the solutions, as well as an evaluation in view of counterparts in existing literature lies beyond the scope of this publication—nevertheless, if such assessment is of interest, the reader is encouraged to consult our publications cited for our solutions in question.

The applications presented below span many typical manufacturing domains and provide examples for all three categories of autonomous industrial robotics discussed in Sec. 2.2.

4.1 Robotic pick-and-place

An autonomous robotic pick-and-place application was established using the already mentioned generic development methodology [73] for part feeding of cable lug components into the fixture of a pressing machine, with the goal of realizing a cable–cable lug assembly. Our task was to transfer complexly-shaped cable lugs into the assembly fixture with the main focus being their detection, localization and manipulation. The physical and digital counterparts of the system are presented in Fig. 4.1.1.

A robot arm was equipped with a simple 2D camera to uncover the application-related uncertainties, which were the actual stable pose, location and orientation of the workpieces, fed in bulk onto a picking surface. This setup is usually referred to as a *semi-structured bin-picking* scenario, which is a relaxed version of the well-

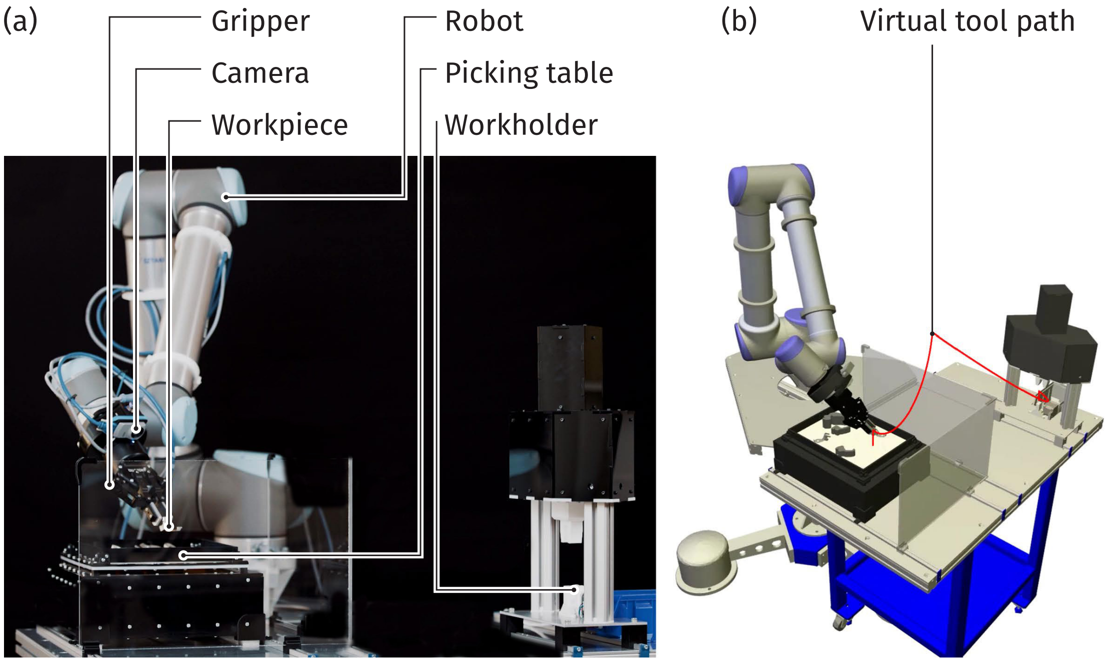

Figure 4.1.1. The physical (a) and the digital counterpart (b) of the pick-and-place system.

known—unstructured—bin-picking problem. For flexible workpiece handling, a vibrating light table was prepared (also serving as the picking surface), capable of rearranging the cable lugs to be picked, as well as providing a homogeneous background for the camera.

In accordance with the DT development methodology, we divided the commissioning and operation tasks to offline and online steps, and prepared the workcell mainly offline, without unreasonably occupying the physical workcell. The offline steps are in this case: (1) the preparation of the DT model (see Fig. 4.1.2), (2) calculating stable workpiece poses for the semi-structured scenario, (3) grasp planning, (4) preparation of the path planner, (5) preparation of the sequence planner, and (6) tolerance analysis for the preparation of twin closeness assessment (see Fig. 4.1.3).

Next, the physical system was implemented, calibrated and verified (for feasibility and twin closeness). Then, the online commissioning steps are the preparation and finalization of the following tasks: (1) capturing an image of the picking surface with the workpieces to be picked, (2) image processing, identification and pose estimation of the workpieces (see Fig. 4.1.4), (3) DT model update, (4) assessing workpiece pickability based on collisions, (5) sequence planning (see Fig. 4.1.5), (6) collision-free path planning, and finally (7) issuing the robot program for task execution.

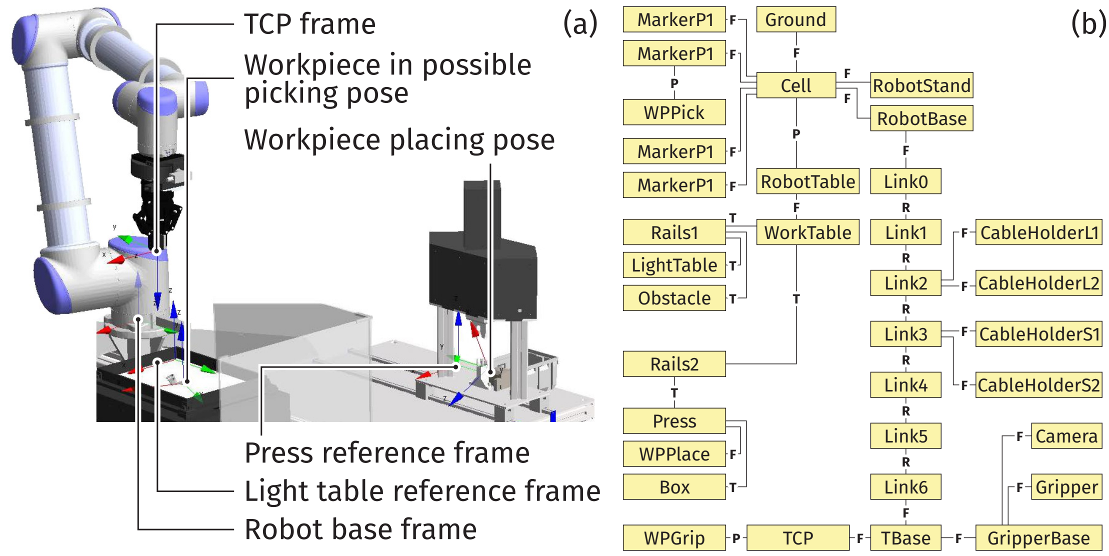

Figure 4.1.2. The kinematic DT model with the main frames (a) and the corresponding simplified kinematic graph (b) of the pick-and-place system.

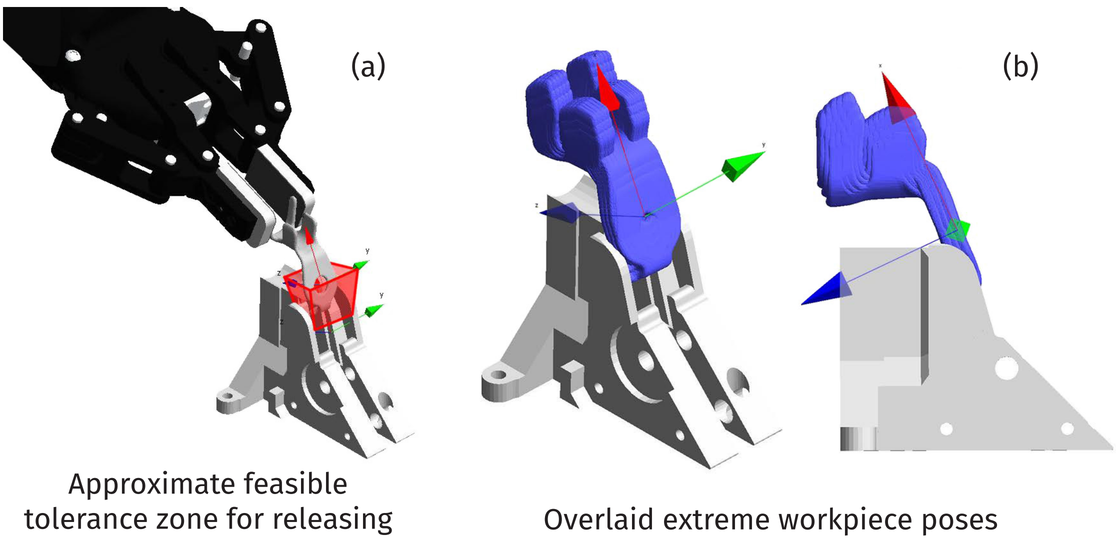

Figure 4.1.3. Feasible tolerance region for workpiece placing (a), and the workpiece geometry transformed using to the results of the Monte Carlo simulation (b).

Lastly, a final verification step is carried out. As sufficient twin closeness was achieved (i.e., the geometrical deviation between the physical and the digital system was within a limit corresponding to feasibility), the physical execution matched the digital one reliably and accurately, meaning that the robotic cell was ready for operation.

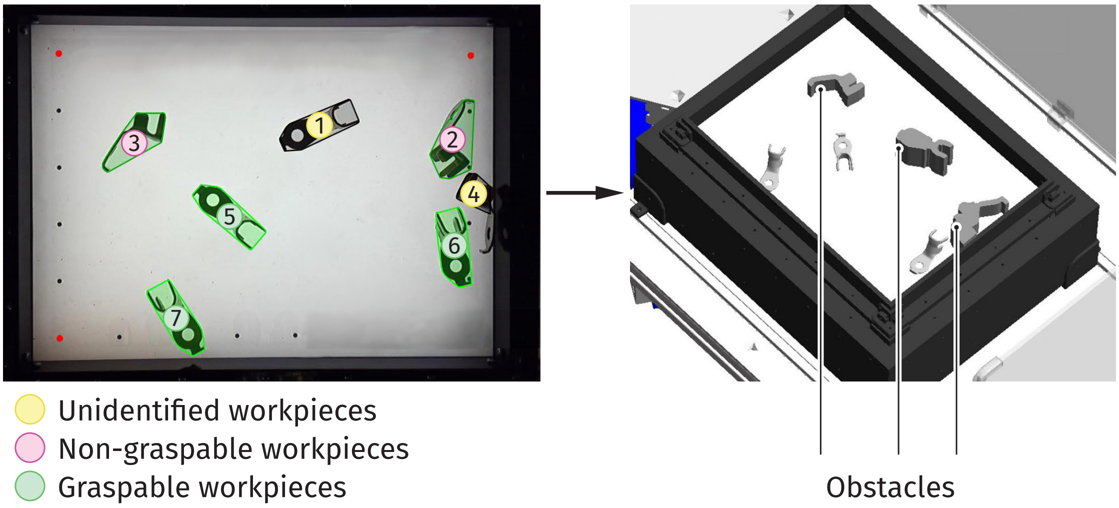

Figure 4.1.4. Resolving uncertainties and DT update based on the captured image.

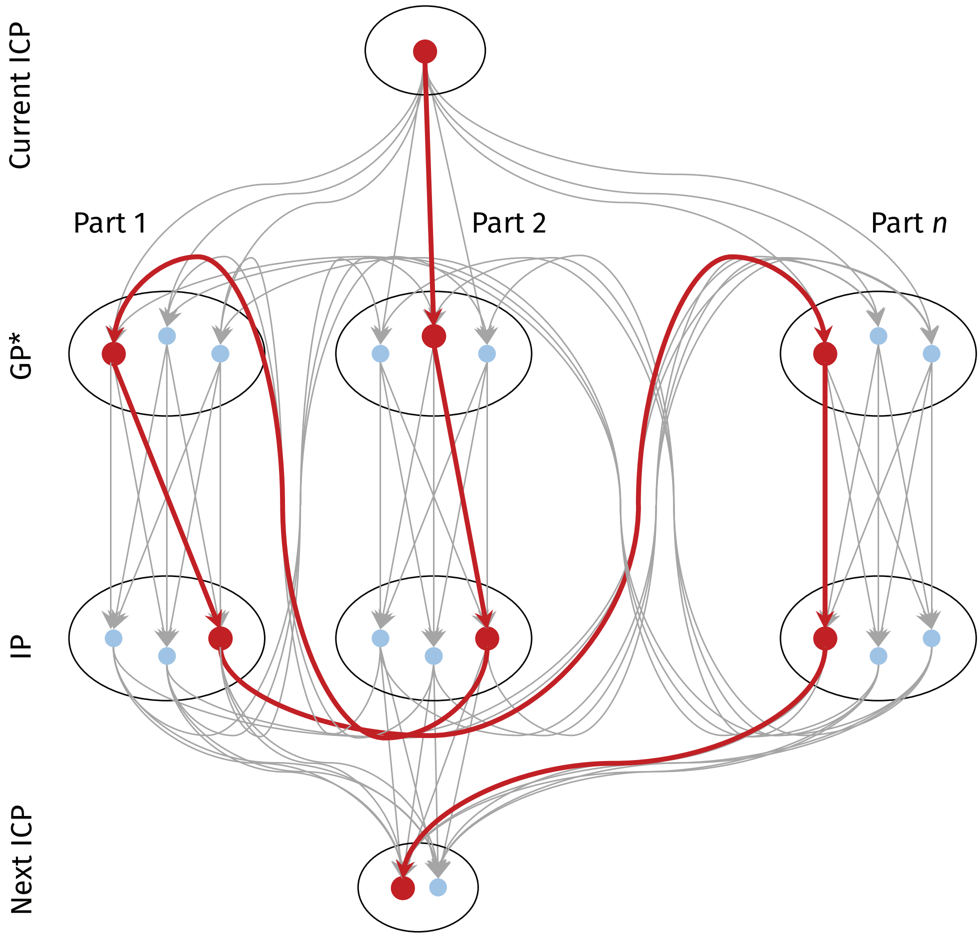

Figure 4.1.5. ProSeqqo model of the pick-and-place application [76].

The steps of operation coincide with the tasks listed in the online commissioning phase, only this time, in every pick-and-place cycle, for the actual workpiece scene present on the picking surface. After each cycle, the workpieces are rearranged in the picking area by activating the vibrating table, and the process starts over with the next image capturing task. The solution is presented in detail in [76].

4.2 Robotic remote laser welding

The development of a new generation of laser sources enabled laser welding with an operating distance (focal length) above one meter, using a laser scanner mounted on an industrial robot. The rotating mirrors in the scanner ensure extremely fast positioning of the laser beam even between distant points on the workpiece. Hence, the emerging technology, *Remote Laser Welding* (RLW) [38] is extremely productive: it achieves process speeds up to 5 times higher than traditional spot welding, while it comes with a lower cost per joint, and removes many earlier constraints on product design by eliminating certain types of accessibility issues [47]. A typical RLW robot consists of a robot arm with 4 revolute joints, two rotating mirrors in the laser scanner, and a lens system to regulate the focal length. Hence, the robot is a redundant kinematic system with 7 degrees of freedom (DoF). The digital twin of the RLW workcell is presented in Fig. 4.2.1, whereas its detailed linkage model is shown in Fig. 4.2.2.

In industrial practice, robot programming for RLW is performed mostly by online teach-in, that is, by manually guiding the robot from one position to the next, in very small steps. This approach is rather time-consuming, it does not allow effective optimization, and hence, easily results in severely sub-optimal robot paths. In order to circumvent these shortcomings, we developed a complete interactive offline programming (OLP) toolbox for RLW with strong optimization capabilities. The overall workflow covers (1) the validation of the input by accessibility analysis, (2) the optimization of the task sequence; (3) robot path planning; (4) the placement of the workpiece in the robot working area; (5) the inverse kinematic transformation that converts the path from the workpiece coordinate system to the robot joint coordinate system; as well as (6) the 3D simulation of the robot path, including collision detection. Finally, the robot program is generated in an automated way [18].

Due to strict constraints on the relative position of the workpiece and the laser scanner, expressed in terms of the laser beam inclination angle and focal distance, as well as the low risk of robot collisions, it was natural to plan the robot motion originally in Cartesian task space. Yet, finding the optimal transformation of the planned motion

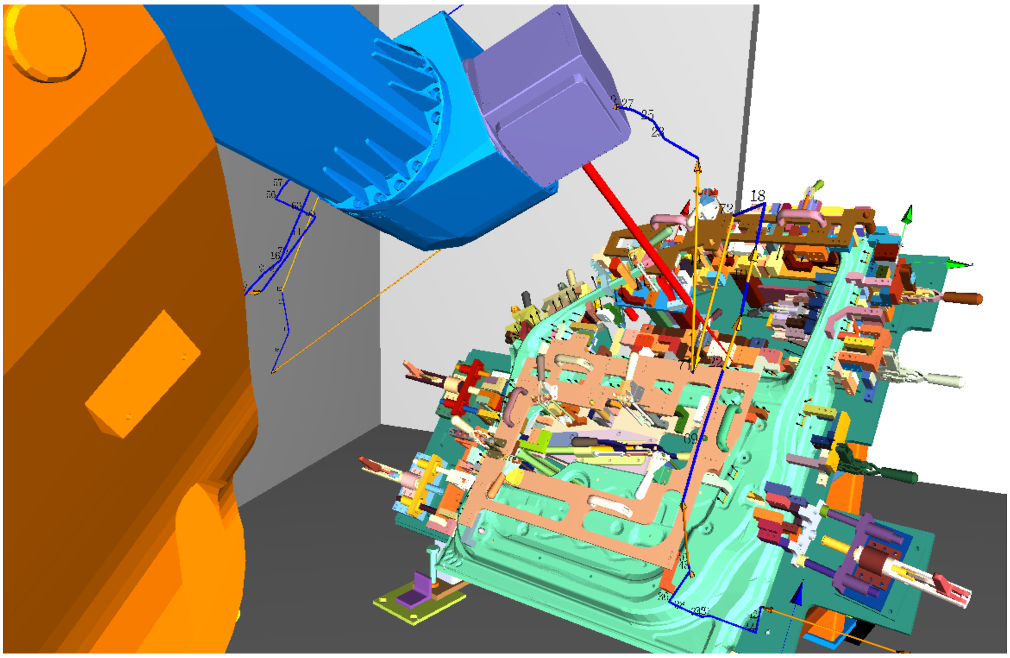

Figure 4.2.1. The digital twin of the robotic remote laser welding cell [18].

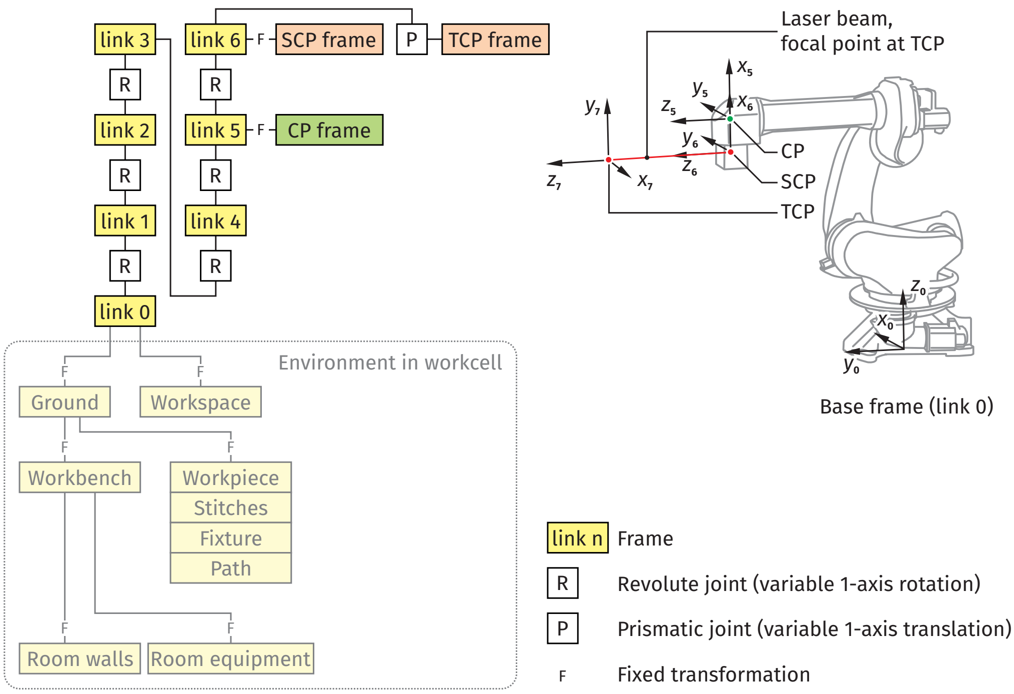

Figure 4.2.2. Linkage model of the robotic RLW cell [18].

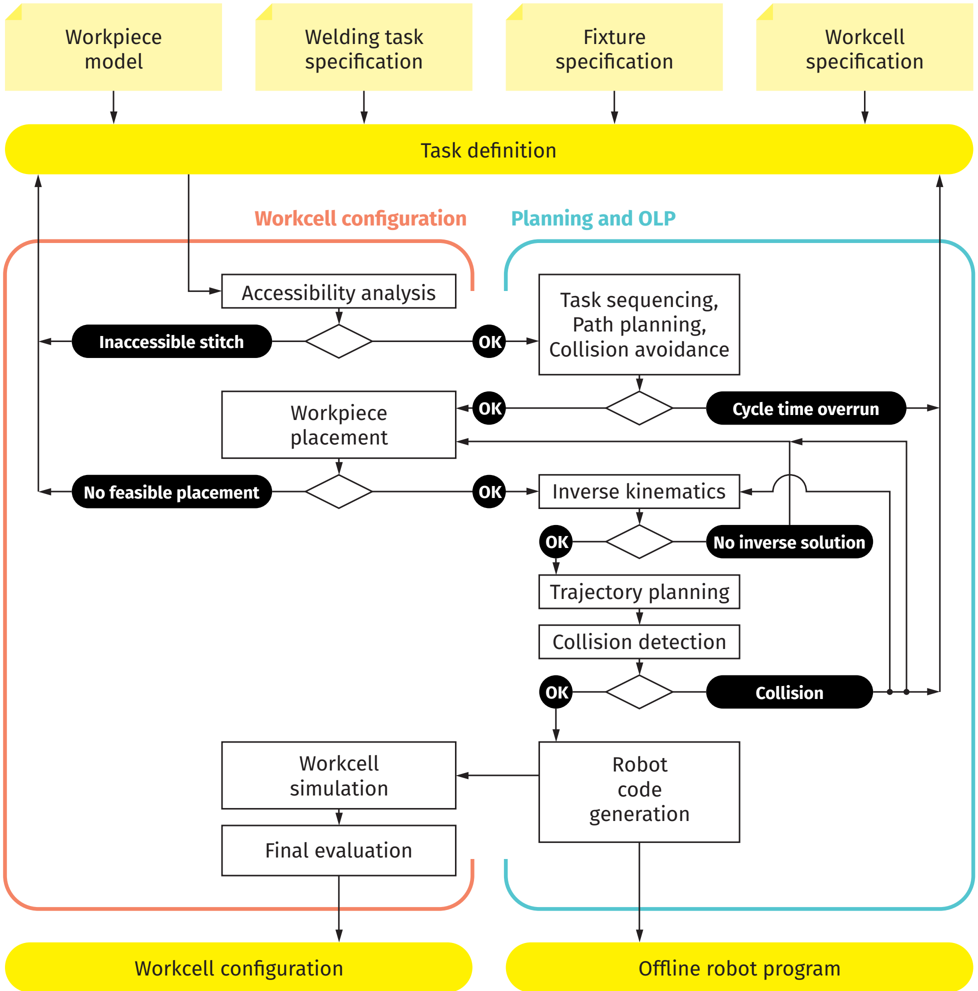

Figure 4.2.3. Workflow in the offline programming system for RLW [18].

to the robot joint configuration space was a challenge, especially because of the redundant kinematics of the RLW robot (7 DoF robot performs 5 DoF tasks). Therefore, we proposed an approach that facilitates bi-directional transition between task and configuration spaces and directly exploits kinematic redundancy to optimize the cycle time [19]. The method was successfully demonstrated in an industrial case study involving a car door assembly, where it facilitated a *first-time-right* implementation of the RLW operation [8].

While robot motion was programmed offline in this mass production environment, real-time sensor information was exploited for process control: in-process monitoring via a photodiode sensor enabled closed-loop control and adjustment of the laser beam parameters to guarantee process quality and compensate any variation of the parts and the process [8].

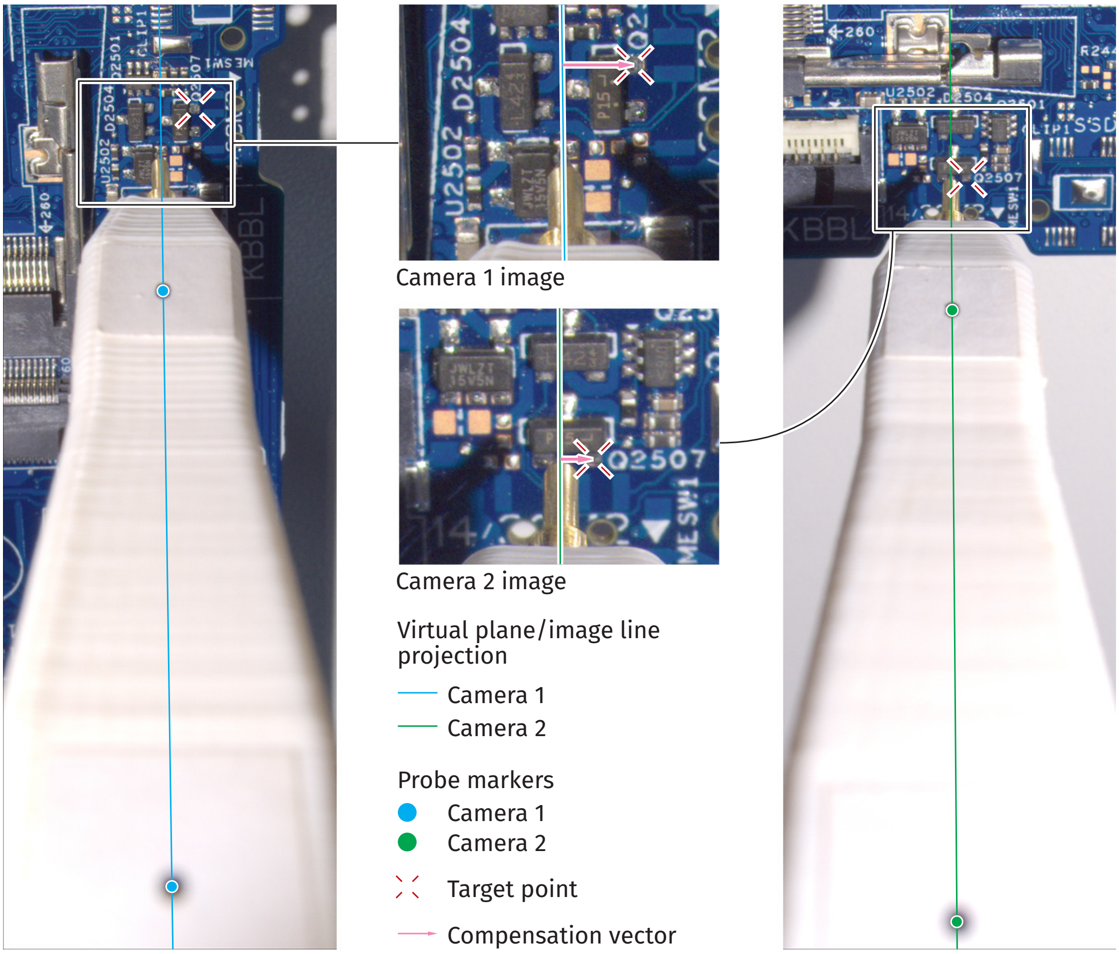

Figure 4.3.1. Robotic inspection: Camera images during the visual servo method for calculating the actual deviation between the reference feature (probe axis) and the target feature (IC lead) [74, 75].

4.3 Robotic inspection

Automatic measurement and diagnosis of *used printed circuit boards* (PCBs) [68] is a challenging task due to the need for precise fixturing of the boards in traditional measuring tools, as well as due to the required PCB schematic and geometric model or drawing of the boards, to facilitate robot programming. Hence, repair shops usually employ human operators to find and identify the root cause of malfunctions of faulty PCBs. In general, these shops face a large variety of products in small batch sizes but with many, frequently recurring product types. Even though measuring operations often contain repetitive steps—seemingly good candidates for automation—automated solutions cannot yet provide such flexibility for repair shops to be worth investing into.

In our inspection scenario, as CAD models are not available for the used PCBs, and twin closeness is insufficient for the required sub-millimeter precision, tolerance growing was inevitable, for which we applied a visual servo-based solution. A new visual servoing probe test method and a corresponding measurement tool were developed that offer a flexible solution for automated diagnostics of used PCBs [74, 75].

The measurements are carried out with a measurement tool (probe) attached to the robot flange. A test-pin—connected to a terminal of a measuring instrument—is mounted on the end of the tool. By iteratively positioning the test-pin to a measurement point until the required precision is achieved, with the help of a novel point-to-line visual servoing approach (see Fig. 4.3.1, [74]), and establishing galvanic contact, electric values can be measured for the particular measurement point. After measuring a set of measurement points, evaluations and decisions can be made based on the resulting electric values.

The system improves the positioning precision of the robot relying on camera feedback (using 2D camera images), enabling the robot to test electronic devices with specific small testing points (in the range of 200–300 micrometers in size). The proof of concept was verified by experiments on motherboards, with a measurement success rate of 99.7%. The solution is currently being introduced in the industry, and a related patent application has already been submitted for the solution [17].

4.4 Robotic grinding

Belt grinding finds frequent use in processing steps as deburring or surface refinement, and plays an important role in industrial production and maintenance. Nevertheless, the noise and particle pollution of the work environment, health hazards through prolonged exposure to vibration and physical strain, as well as the repetitive nature of operations make it worthwhile to delegate grinding tasks to robots wherever feasible [84].

This was also the motivation behind the request of an industrial client for the robot-enabled rebuilding of a belt grinding station along with layout redesign to accommodate new types of workpieces [20]. The task to be performed was centered around de-burring of metal castings with a planar parting line, with some points of the casting not being reachable by the given grinding tool (i.e., possibly requiring—typically manual—rework with other tools at a separate station). The required solution had to address several aspects: (1) calculating a planar grinding pose trajectory and determining which sections of the workpiece are reachable with the available belt grinding unit;

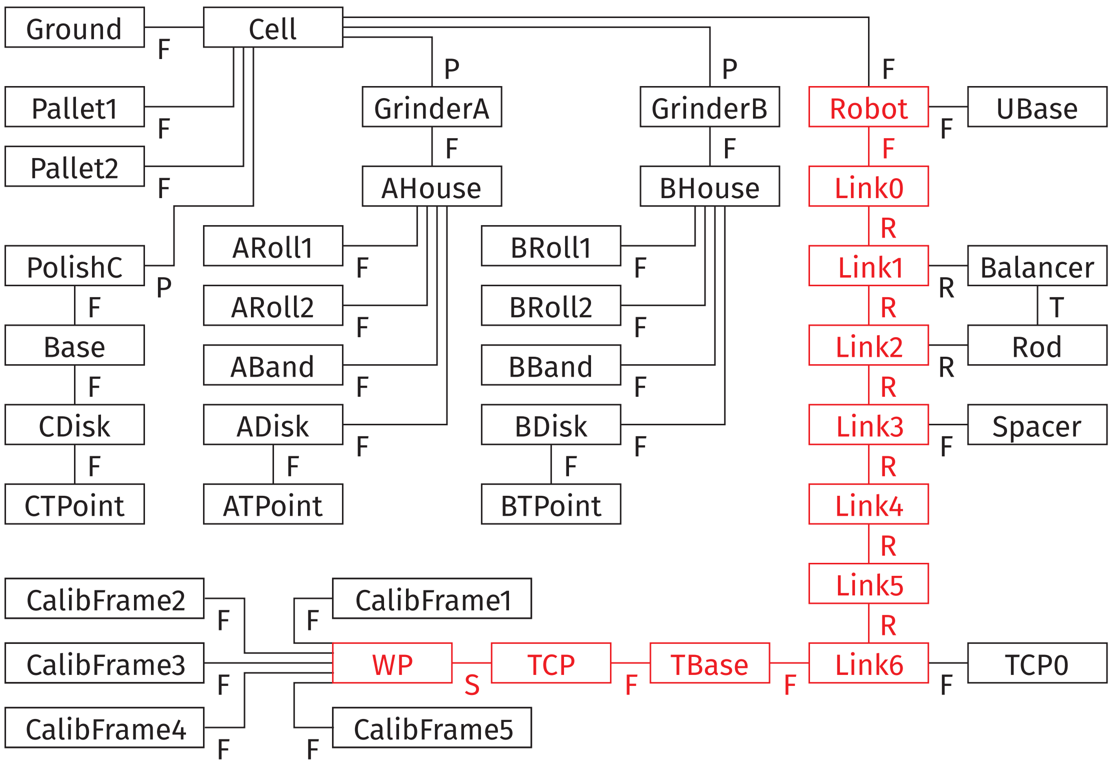

Figure 4.4.1. The core linkage model of the digital twin of the robotic grinding cell (the robot's linkage model is in red color).

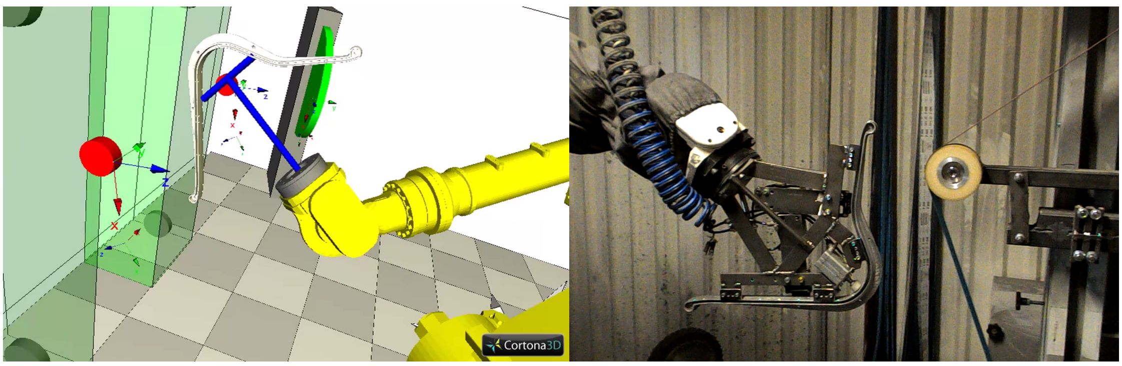

Figure 4.4.2. Robotic grinding: Digital twin and the real process.

(2) elaboration of a digital model of the robot grasping the workpiece, the workpiece itself with a pre-determined pose path attached, and the grinding unit with all associated appliances that may present obstacles; (3) evaluation of the virtual model for feasible collision-free operation with the selected workpieces and paths, and (4) matching of virtual (as-designed) and physical (as-built) implementations of the grinding cell for accurate planning and execution of robot motion for the actual workpieces.

The first step of the solution was built on the CAD model of the selected workpiece: a robot path was generated by subsequent contour expansion and contraction of the nominal workpiece section at the parting plane (i.e., two subsequent Minkowski morphological operations [22]), determining a series of nominal poses to be passed by the robot, as well as identifying the sections unreachable by planar use of the grinding tool [20].

In the next step, a linkage-based DT of the entire proposed grinding cell was built up, comprising models of the selected robot, belt grinding appliances, and the workpiece (see Fig. 4.4.1). Feasibility of collision-free path execution of selected workpiece types was tested, revealing critical points in cell layout choices, resulting in further iterations of layout redesign and DT assessment.

Finally, the physical implementation of the cell was built up at the client's site (see Fig. 4.4.2). Measurements were taken to calibrate the parametric DT of the cell design, and to adjust the virtual model to match physical reality within the required tolerances. Having obtained a calibrated DT, a nominal robot path was recalculated for the as-built cell layout and actual workpiece geometry.

While the client was satisfied with the resulting robotic application, an extension of the original solution is now under preparation, to exploit the geometric reserve of more complex path planning based on an enlarged set of feasible workpiece–grinding belt contact points and relative orientations.

4.5 Assembly planning, collaborative assembly

Mechanical assembly is an application domain characterized by an intricate and strong interconnection between task planning (also called macro-level planning in the literature of computer-aided process planning, CAPP[70]) and motion planning (micro-level planning in CAPP). Beyond a variety of aspects involving the product structure, assembly technology, fixturing and tooling, tolerances, quality, and production economics,

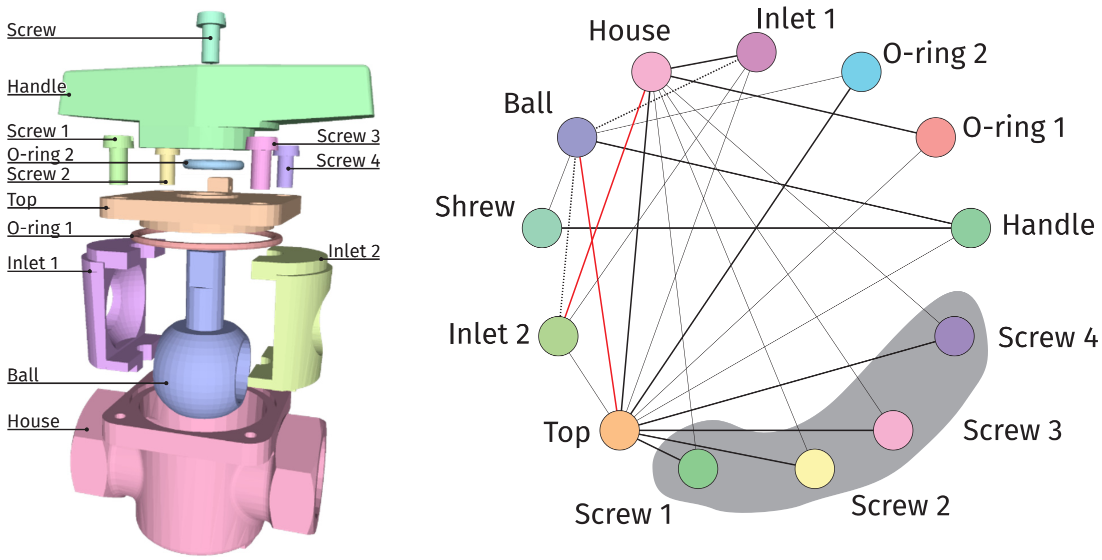

Figure 4.5.1. Automated generation of the liaison graph for the feature-based representation of a product in mechanical assembly.

4.5

task planning must also consider constraints stemming from geometry that cannot be readily extracted from engineering knowledge bases, but must be laboriously discovered during motion planning. These involve accessibility constraints that depend on product, fixture, tool geometries, as well as the motion of all these objects required by assembly technology. We proposed a constraint model and an associated constraint-based solution approach for task planning (macro-level planning) in mechanical assembly based on a generic feature-based representation of the product and the assembly operations (see Fig. 4.5.1), which places special emphasis on capturing the feedback from the motion planner, and hence, on the integration of the approach into a complete CAPP workflow [36, 37]. The algorithm adopts a so-called logic-based Benders decomposition approach to recognize potential geometrical issues during the assembly process and to formulate constraints that prevent the occurrence of similar issues in future iterations. The computational efficiency of the approach was boosted by disjunctive programming techniques [30].

The *assembly plan* provided the basis for organizing teamwork in a one human–one robot collaborative assembly setting. The roles shown in Fig. 3.6.2 were initially assigned manually. Next, an assembly workcell was set up and equipped with the required fixtures and tools (such as gripper, screwdriver, wrench). Motion programs to execute the individual robotic assembly tasks were generated offline. Similarly, assembly instructions were generated for the tasks which were assigned to the human

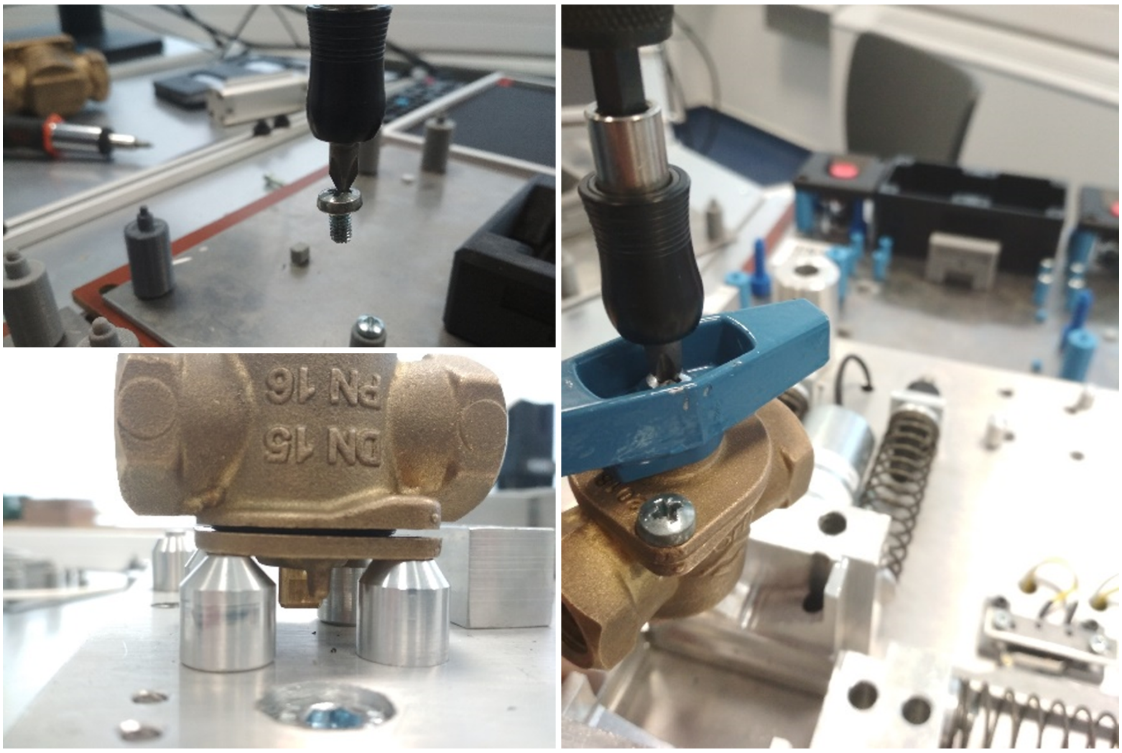

Figure 4.5.2. Errors at execution time of a robotic mechanical assembly plan.

worker. Here, alternative instructions were generated to different skill levels: more concise for highly skilled workers, and content-rich instructions with drawings, pictures and videos for less skilled ones. Finally, the HMIC system (see Sect. 3.6.3) was filled in with the assembly plan and the instructions controlling the robot and the worker.

HMIC arranged a smooth, well-organized collaboration of the robot and the worker, whose *safety* was warranted by a point cloud-based safety function. Nonetheless, as in any normal industrial environment, some errors did occur at execution time (see Fig. 4.5.2). The appropriate handling of these situations, the detection and correction of errors, and the recovery of the execution of the assembly plan require yet another layer in the HRC control protocol. These issues are in our future research focus.

4.6 Smart machining

Digital twins with real-time capabilities open the door to new sensor development, such as combining contactless perception with real-time, geometry-based collision prediction. Our linkage-mechanism-based DT model (see Sect. 3.1) was adopted for

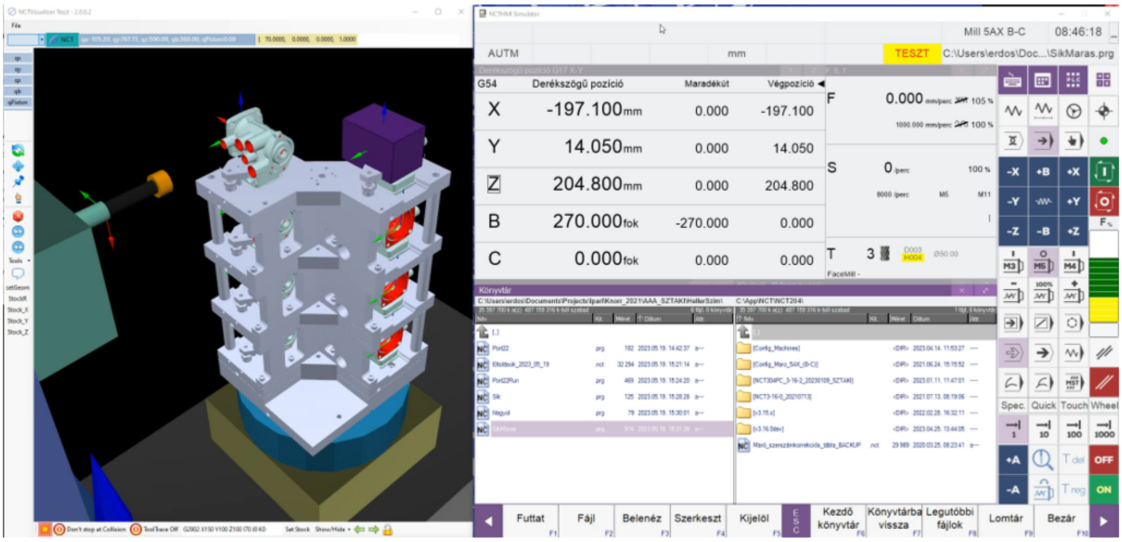

Figure 4.6.1. The DT-enhanced NC machine tool controller.

NC machining as built-in modules of NC controllers. The DT-enhanced controller has three extra functionalities: (1) a machine model motion simulation, (2) collision test, and (3) material separation simulation.

Strict limits apply to the response time of the software modules, as they are integrated into an NC machine controller. Typical cycle time limits of the modules vary between 1–10 msec. The modules are implemented in a program package using OpenGL-based three-dimensional graphics programming functions on the Windows operating system. The digital twin model is being developed in cooperation with *NCT Ipari Elektronikai Zrt.*, a company designing and producing CNC controls and servo drives. The machine model motion simulation and collision test modules are developed by HUN-REN SZTAKI, while the material separation simulation module is developed by NCT. The modules have already been integrated and fine-tuned, and the company has presented the machine digital twin model product integrated in its controller at several exhibitions (EMO 2021 Milano, Italy[1]; Days of Industry, 2022, Budapest, Hungary[2]). This generic real-time DT model can be further utilized for robotic workcell modeling and processing as well.

The above DT-enhanced machine tool controller was applied in *near-net-shape manufacturing* (NNS) where the overall objective is to create blank parts with complex functions and geometries by non-subtractive processes as close to their required final geometric shape, surface and material properties as possible. Hence, the product

[1]https://emo-milano.com/en
[2]https://iparnapjai.hu/en/

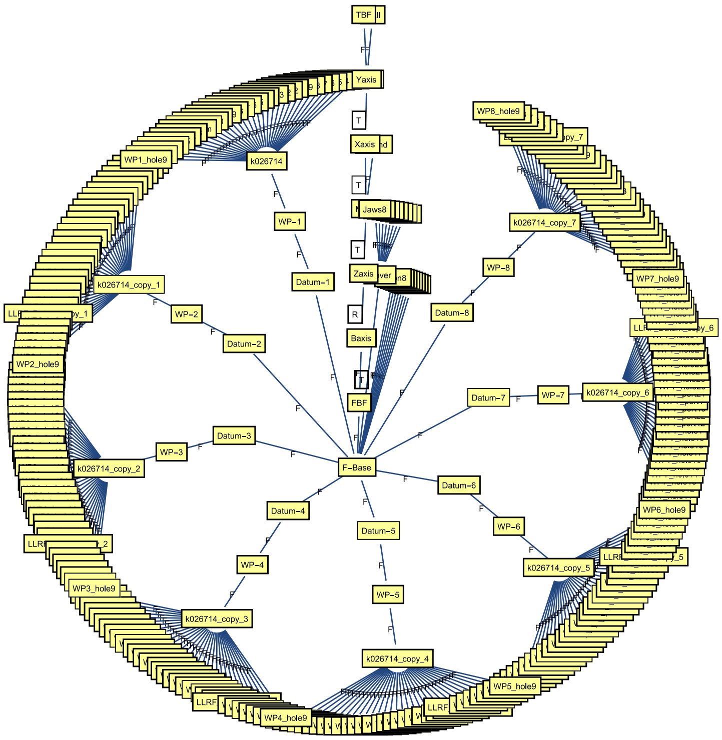

Figure 4.6.2. Linkage mechanism of near-net-shape manufacturing.

with its functional features can be extracted in the finishing step with minimal material removal. The final shape is typically given by machining, but other finishing processes can also be applied.

We have developed a multi-operation *blank localization* method to fit the final product geometries into near-net-shape blanks [11]. Here, groups of machining features are located, subject to tolerance intervals on their relative positions, and a lower bound on the machining allowance, which accommodates for uncertainties of measurement and machining. The tolerance error, i.e., the deviation of the resulting dimensions from the center of the tolerance intervals, is minimized. The blank localization problem was formulated as a convex quadratically constrained quadratic program that could be efficiently solved for parts with real-life complexity, as it was demonstrated by a case study from the automotive industry. The NC programs, which were transformed as a result of the blank localization, were validated by virtual machining, using the DT-enhanced controller. Fig. 4.6.1 shows the setup, while Fig. 4.6.2 shows the DT of the complete machining scenario as a complex linkage mechanism. This DT includes the model of the machine tool, the tool, all elements of a rotating fixture which contains eight parts to be machined, as well as the machined features of the parts.

4.7 Summary of the applications

Below we summarize the various autonomous robotic applications according to the three categories defined (see Sect. 2.2), and the six enabling technologies (see Ch. 3) applied in Tab. 4.7.1 and Tab. 4.7.2, respectively. In the tables the applications are referred to as follows: (A) picking and placing, (B) remote laser welding, (C) inspection, (D) grinding, (E) assembly, and (F) machining.

	A	B	C	D	E	F
relieve and delegate	×	×		×		
augment and extend			×			×
include and integrate					×	

Table 4.7.1. Summary of the applications according to the categorization of autonomous industrial robotics.

	A	B	C	D	E	F
linkage-based DT	×	×		×	(×)	×
twin closeness	×			×		×
perception and learning	×	×	×			×
process and motion planning	×	×	×	×	×	×
servo control		×	×			
teamwork support					×	

Table 4.7.2. Summary of the applications according to the applied enabling technologies.

5 Conclusions and outlook

The production line, as a key innovation of the previous industrial revolution, is reaching its limits, and manufacturing faces a growing need for dramatic paradigm shifts: maintaining mass production efficiency while permitting customization on a lot-size-one level, industry-wide roll-out of digitalization, cloud-manufacturing systems, cyber-physical production systems enhanced by AI and machine learning, the pressure for de- and re-manufacturing, and the scaling-up production of highly integrated intelligent consumer products. Autonomous robotics can provide a feasible answer to these challenges.

In the paper, we have suggested a classification scheme for industrial autonomous robotics, and presented a set of generic enabling technologies which were developed in the course of the last 10 years at HUN-REN SZTAKI. The application of these technologies across six different domains of manufacturing were also briefly presented. The entire picture rather summarizes the experience we have accumulated in the past period when developing various robotic solutions with some sort of autonomy. Hence, it is based on what we have seen and achieved so far.

However, many of the possible forms of autonomous robotics have not yet been exemplified in our research, not to speak of industrial practice. In order to serve as a point of reference, here we suggest directions for future research. *Safety* is the first concern. Although advanced safety methods and mechanisms have already been developed, most of these methods are established in a laboratory environment. The hardware utilized are prototype-level devices that cannot be transferred to industry directly. In hindsight, it seems as if safety and autonomy were forever at odds [24]. We are convinced that more mature devices at a higher Safety Integrity Level (SIL) are needed to further improve and exploit the research results. Moreover, the feasibility of the HRC solutions have been well evaluated, but the safety performance needs to be assessed systematically. For example, stability, robustness, response time, redundant safety, backup solutions, and emergency handling need to be evaluated in a structured and standardized way [54].

In any HRC setting, the model of the human worker should be integral part of the digital twin [72]. Continuous observation of behaviors and models of human disposition and emotion at the workplace in industry-ripe applications of execution control at manufacturing workstations are still missing. There is a need to elaborate and populate models of human workforce and develop task execution control and communication approaches that can establish individual worker preference profiles, pick up transient changes in the state of the individual worker agents, and tune both communication and acquired models accordingly.

Advanced human–robot interfaces, especially those conveying work instructions, often provide adaptability to the given worker in discrete steps, namely, by skill level categories (see Sect. 3.6.3). Adaptation to the worker's current (and changing) fitness for the current task is, however, not part of industrial practice. The devices keeping track of the worker's awareness primarily serve safety purposes only. AR-based in-situ decision support to workers in dynamic HRC assembly environments deserves more attention to be both intuitive and free of additional mental stress. Work instructions need to be adaptive to not only the changing competence level of individual workers but also the declining focus and concentration during the day or within the week.

Collaborative robotic workcells are getting more and more common in industrial applications. The control of such cells employs advanced AI methods and techniques which support adaptive, flexible, efficient and safe human–robot collaboration. Indeed, AI provides the key enabling technologies for integrating the best capabilities of the two kinds of actors. However, the application of AI in cobot cells—where humans and machines work in close proximity—comes along with a number of new *ethical* hazards and risks as well. Recently, we have elaborated a novel workflow for designing technically and ethically correct cobot workcells [57]. In this workflow, one track is responsible for configuring the workcell, another one for controlling its behavior, while the third track explicitly accounts for all relevant ethical considerations. In an industry-motivated case study, we also presented how a cobot cell uses advanced sensing, mixed reality as well as symbolic AI planning techniques for realizing complex assembly tasks. In general, with the advance of digital technology, the gap between human and machine communication is narrowing. Diversification of the workforce and machinery will become a forefront issue in advanced manufacturing industries. New concerns will be raised about changes in the interaction between various people and machines due to the differences in age, attributes and skills, and the impact of such changes on society, particularly the working environment.

Advanced execution control, as discussed in Sect. 3.6.2, requires *handling of exceptions*, *emergency* and *recovery*. Even though some methodologies address early fault prevention and detection, this is not necessarily equal to continuous feedback regarding operation results. Not only does this often result in the costly temporal and spatial separation of training from work execution, it also hampers orientation of the worker in ad-hoc work situations, e.g., in construction of individual products, or in the maintenance of poorly documented legacy equipment. Since training and quality check are typically separated from task execution, gradual skill development, live assistance and real-time feedback are obstructed. Industry-proof integrated processes of *learning-by-doing*, adequate in the context of HRC must be elaborated where performance evaluation results (including those of quality checks) are fed back to support the improvement of the overall team. In any learning-by-doing scheme, the safety requirements must be continuously observed.

However, we have not yet observed the widespread transfer of disruptive AI technologies into autonomous industrial robotic applications which address the above problems. Breakthrough is still to be expected in the fields of embodied AI and cognitive robotics, in collective intelligence and real human–robot teamwork within industrial settings. Reasonable and explainable AI are also still in debt with providing industry-proof solutions, just as trustworthy, responsible AI. The consensus among the public, numerous AI researchers, and authorities is clear: the exceptionally rapid advancement of AI entails significant risks that demand immediate and decisive action [2], also in the field of robotics. We are aware of these issues which define a new agenda for the research of autonomous robotics [57, 56] which can, however, be based on some of the technological developments reported in the paper.

We can but hope that foundational models and generative AI can help overcome the issues of raising and maintaining trust towards autonomous robots in industrial settings.

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