Ontology-based Digital Twin Framework for Smart Factories

Snehal Walunj
German Research Center for Artificial Intelligence
Kaiserslautern, Germany *snehal.walnuj@dfki.de*

Michael Sintek
German Research Center for Artificial Intelligence
Berlin, Germany *michael.sintek@dfki.de*

Parsha Pahlevannejad
German Research Center for Artificial Intelligence
Kaiserslautern, Germany *parsha.pahlevannejad@dfki.de*

Christiane Plociennik
German Research Center for Artificial Intelligence
Kaiserslautern, Germany *christiane.plociennik@dfki.de*

Martin Ruskowski
German Research Center for Artificial Intelligence
Kaiserslautern, Germany *martin.ruskowski@dfki.de*

Abstract

In modern smart factories we have multiple entities that interact with one another, such as worker-assistance system, robot collaboration and their corresponding software modules. To facilitate seamless cooperation between those subsystems, it is beneficial that they all have access to one coherent environment model. Hence, we propose an ontology-based Digital Twin that allows semantic representation of all important parts of such a scenario. It allows uniform access for different application components such as intention recognition and robotic action planning. Furthermore, it provides information tailored to the needs of those different components, e.g., via different *zoom levels* and *affordances*.

Keywords: Digital Twin, Ontologies, Semantic Web, Smart Factories, Robotics, Semantic Zoom

1. Introduction

Smart factories, also known as Industry 4.0 or the Fourth Industrial Revolution, are modern manufacturing facilities that are highly automated, connected, and intelligent. Smart Factories rely on technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning, robotics, and big data analytics to increase productivity, efficiency, and profitability. Flexible production in modern Smart Factories requires effective support of human workers and smooth cooperation with assisting robots. However, in a factory scenario where the worker performs manual tasks, the hands are often not free to interact with assistance systems. Voice commands are not practical either due to factory noise. Hence, to provide well-adapted and acceptable support, both a worker assistance system (supported by intention recognition) and robotic action planning need to anticipate the worker's future activities. To improve efficiency, productivity, and collaboration between humans and machines, leading to a more efficient and effective manufacturing process, semantic technologies play an important role in a Smart Factory. Semantic technologies use a standardized format to structure and describe data, making it easier for machines to understand and process.

In this paper, we consider semantic technologies for enhancing a Digital Twin of the Smart Factory, which represents the physical factory and its processes in a virtual world. The Digital Twin can be used to simulate different scenarios, test changes to the factory layout or equipment, and optimize the factory's performance. This semantics-enhanced Digital Twin allows to give several software components like robot action planning and intention recognition [22] uniform access to the Digital Twin. It is also capable of providing these different components with exactly the information they need. This is done by introducing *zoom levels* (explained in Section 5) and *affordances* (explained in Section 6).

The semantic Digital Twin is built by reusing existing, standardized ontologies that are extended to be useful to represent Smart Factories and their Digital Twins. The ontology-based model of the Digital Twin thus constitutes a semantic environment model. API access to knowledge represented in this semantic environment model and stored in standard triple stores is facilitated by using the SPARQL query language [9] and SPARQL protocol [6]. By using triple stores that support user-defined inferences, advanced functionalities such as automatically inferring facts like `on(screwdriver, table)` from basic spatial relations are made possible, which are important for robot action planning.

The remainder of this paper is structured as follows: State of the Art for Smart Factory and Semantic Digital Twin in Sect. 2, Scenarios in Sect. 3, Digital Twin in Sect. 4, Ontology-Based Environment Model for Digital Twin in Sect. 5, Implementation and Evaluation in Sect. 6, and finally Conclusion and Future Work in Sect. 7.

2. State of the Art for Smart Factory and Semantic Digital Twin

Smart Factory

In recent years, a paradigm shift from traditional mass-production to mass-customization of products has become apparent [31]. Industries are striving for this mass-customization of products in order to achieve lower unit costs per customized product. The greater the variety of products, the more important it becomes to support the human workers producing them. A flexible production environment is necessary in this regard. Smart Factories are intended to provide such a flexible production environment.

Over the past few years the state of the art in Smart Factories is constantly evolving as new technologies are emerging and existing ones are improving. [27] presents an overview of the state of the art and future trends for Smart Factories. Industry 4.0 was introduced during the Hanover Fair in 2011 in Germany. It aims to create Smart Factories and realize more efficiency, flexibility and reliability and mainly includes enabling technologies such as cyber-physical systems (CPS), Internet of Things (IoT) and cloud computing. Furthermore, AI technologies such as machine learning, computer vision and deep learning are being used to automate and optimize industrial processes, improve quality control, and enable predictive maintenance. [16] presents a review of AI applications in Smart Factories. Advanced information and communication technology such as cognitive agents, swarm intelligence, and cloud computing are used to integrate, organize, and allocate the machine resources [8]. Furthermore, big data analytics is also trending more in smart manufacturing. It is, for instance, being used to improve quality control by analyzing data from sensors and other sources. Nagorny et al. [20] give a review of Big Data application in smart manufacturing to optimize key performance indicators, diagnose, predict, and optimize design. Processing such big data requires specific techniques to be effective and efficient, which refers to how well the outcome of the performed data processing task meets the expectation. In [30] a new vision of Smart Factories under the label of Production Level 4 was presented, which is focusing on production bots and skill-based manufacturing systems in a fully networked production. This work pushes topics such as Industrial Internet of

Things (IIoT), autonomous production further ahead. One of the applications of automation in production is autonomous robots. The usage of robots in industry was proposed in 1961. [10] deals with the technology of autonomous mobile robots (AMR) and their implementation on a Smart Factory production line. The Smart Factory serves as an environment wherein humans can collaborate with robots to accomplish various tasks. Robots can also be used for assisting humans in situations such as a manual assembly process or a maintenance task [4].

Digital Twin

Digital Twin (DT) is among the key trends in modern manufacturing systems. The term Digital Twin was first coined by Michael Grieves a decade ago, introducing it as "a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physically manufactured product can be obtained from its Digital Twin" [7]. In simple terms it can be defined as a digital replica of any real entity which serves as a platform for developing, changing or inspecting it without actually interacting with it in the real world. A cyber-physical system consists of both a physical part and a complementary digital part, capable of mimicking its physical counter part. In order to be able to mirror or mimic the real world, which also can be termed as Physical Twin, the DT needs to be equipped with information that represents the real-world in the virtual space. Together with information, real-time data linkage is also an eminent part of this cyber-physical system [2] especially in situations such as an assembly process or a maintenance task. In [18] a model-based definition of Digital Twin was proposed for computer-aided design models by enhancing model inter-connectivity with spatially related non-geometric data. This helps CAD modelers and consumers to readily utilize the CAD information simplifying their job. Thus, Digital Twins are applicable for diverse purposes and at various stages in the production.

Semantic Digital Twin

In previous years, Digital Twins were combined with semantic technologies like RDF [14], RDFS [8], OWL [11] ontologies, and other semantic web technologies like reasoning. The PhD thesis "Semantic Digital Twins in the Industrial Internet of Things" [1] describes data models for Digital Twins based on a semantic version of the Asset Administration Shell (AAS), which is the industry standard to reach a common grammar for representing industrial assets. "Semantic Digital Twins for Retail Logistics" [15] proposes semantic Digital Twins for retail store environment, connecting a symbolic knowledge base with a scene graph, which provides a realistic 3D model of the store. Reasoning for question answering is performed with the help of Prolog.

In "Semantic Digital Twins for Organizational Development" [29], the authors describe semantic Digital Twins for organizations, where both social structures and physical setups like buildings, factories, computers etc. are taken into account. "A Holistic Digital Twin Based on Semantic Web Technologies to Accelerate Digitalization" [19] deals with a Digital Twin using Semantic Web representations of supply chains deploying and manufacturing semiconductors, where the ontology is based on existing W3C recommendations like a sensor ontology. "Scaling Knowledge Graphs for Automating AI of Digital Twins" [26] introduces Digital Twins that use machine learning components where underlying data sources are linked with the help of semantic knowledge graphs.

"Internet of Things Ontology for Digital Twin in Cyber Physical Systems" [32] proposes an ontology to represent a Digital Twin in the context of Cyber Physical Systems (and thus Industry 4.0 and Smart Factory) and embedded systems. This ontology covers the main concepts for the mapping of physical devices as well as the concepts involved in the development of the Digital

Twin, and it can also be used for graphic visualization of the Digital Twin.

In “A design framework for adaptive digital twins” [5], a new DT design framework was developed that uses ontologies to enable co-evolution with complex engineering systems by capturing data in terms of variety, velocity, and volume across the asset life-cycle.

3. Scenarios in Smart Factory

(a) Part of a Smart Factory (for Smart Maintenance)

(b) Example robot

(c) Manual assembly module

Fig. 1. Smart Factory

In modern smart factories effective support of human workers and cooperate with assisting robots are two crucial aspects, which obtain more production flexibility. Thus, to have a robust and reliable support, both a worker assistance system and robotic action planning need to anticipate the worker’s future activities, which can be facilitated by using one coherent environment model. The feasibility of the approach will be demonstrated with the help of the following two scenarios in a Smart Factory environment, in which an assisting Robot carries spare parts and necessary tools to worker for accomplishing a task in the production environment:

(1) Smart Maintenance Scenario:

Smart Maintenance (also known as predictive maintenance) is an approach to detect and resolve a failure, which uses data analysis and machine learning algorithms to predict when equipment is likely to fail and schedule maintenance proactively, before a breakdown occurs. Smart maintenance relies on the use of sensors and other data collection devices to gather information about equipment performance, such as temperature, vibration, power consumption and noise levels. This data is then analyzed using machine learning algorithms to detect patterns and anomalies that may indicate potential problems. When an anomaly is detected through predictive maintenance, there are several steps that can be taken to solve the issue. The first step is to investigate the anomaly and try to understand its root cause. Once the root cause has been identified, it is important to assess the severity of the issue. This can help to determine the appropriate course of action, such as scheduling maintenance or shutting down the equipment to prevent further damage to the machine. Prioritizing maintenance activities is the important next step in smart maintenance scenarios. Once the priority issues have been identified, maintenance activities can be scheduled based on the equipment’s availability and the maintenance team’s workload and maintenance activities such as repairs, replacements, or adjustments to the equipment are taken. Additionally there is a certain method that the worker must follow to carry out the maintenance or repairs which can be time consuming and effort intensive. Also the worker must have knowledge about the failure , the circuit charts and be trained to solve the particular problem.

Finally, after maintenance activities are completed, it is important to monitor the equipment to ensure that the issue has been resolved and that the equipment is operating as expected. In order to support the worker in such maintenance scenarios, assistance systems [17] can be developed that leverage system knowledge and provide context-specific assistance. Fig. 1a shows the demonstrator for the Smart Maintenance scenario; the autonomous mobile robot is shown in Fig. 1b.

(2) Manual Assembly Scenario:

Despite major developments in modern Smart Factories, there are production processes that still involve a certain degree of manual work. For instance the worker manufactures a product, which can be assembled in a variety of orders. On the other hand a mobile robot can support the worker by carrying the spare parts or tools. The goal in such manual assembly scenario is to use semantic information from the Digital Twin to assist the worker. Through an intelligent assistance system, the worker can be supported more effectively and in a user-friendly manner by enriching the existing set of data with context-sensitive information. Fig. 1c shows an example of a manual work station, which is used in this work to demonstrate the feasibility of human robot cooperation in a manual assembly task through worker assistance and a mobile robot. Since different assembly sequences are possible in such a scenario, it is a challenging issue to determine which sequence the worker is following and in which step he is at the moment. Thus it is important to have a common understanding of the assembly process, the relationships between its tasks and sub-tasks and the corresponding objects or resources used at each assembly step. The manual work station itself is also modeled in the ontology based environment model of the Digital Twin.

4. Digital Twin

Our Digital Twin is modeled within Unity software. Since CAD models are readily available for most industrial components and even for the robot, they are used for building demonstrators in the Smart Factory environment in Unity. This helps us model and visualize every component of the system and its 3D correspondences with other features of our human-robot collaboration system. For example, the 1:1 scaled 3D environment is useful for simulating the robot navigation and identifying obstacles in its path. Also, each component is identified by the common taxonomy used by the whole system.

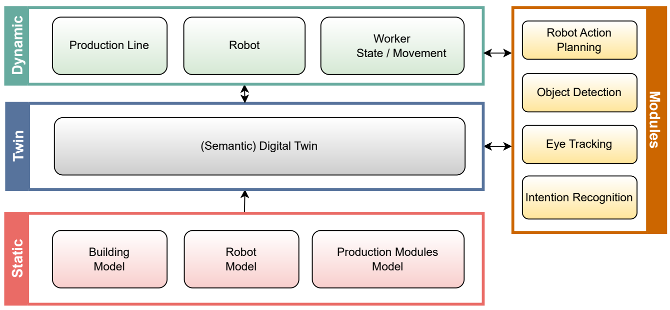
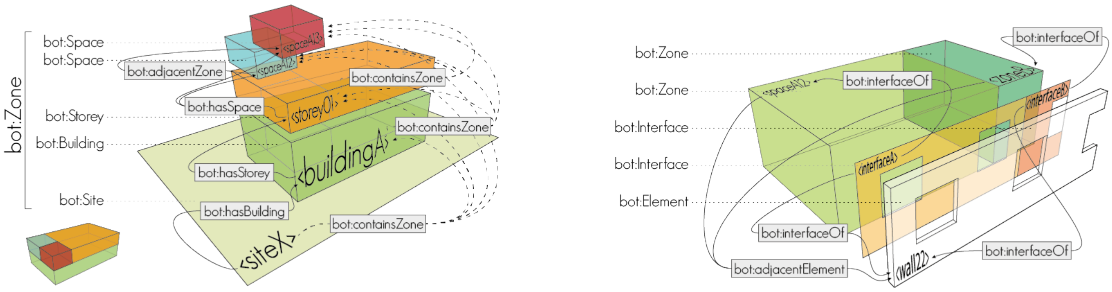


Fig. 2. System architecture for Smart Factories

Fig. 2 shows our general system architecture for Digital Twins. The lower lane contains the static data sources that are used to create the Digital Twin, like the models of the building and the production modules, and the robot model. The upper lane contains the dynamic sources that are used to interact with the Digital Twin at run time. Furthermore, there are some software modules that interact both with the dynamic sources and the Digital Twin, and also with each other, like robot action planning, object detection, and intention recognition.

5. Ontology-Based Environment Model for Digital Twin

For representing the Digital Twin, we use existing and well established ontologies. The model has to aggregate information about buildings, rooms, factory objects like production lines, tools, and also humans, robots, etc. We therefore identified the Building Information Modeling (BIM) [3] as a solid source for all building-related aspects of a factory setting, ready to be automatically mapped and integrated into our model of the environment. We chose the “Building Topology Ontology” (BOT) as the base of our ontology as it is a W3C standardized ontology and widely accepted in industry [28], see Fig. 3.



(a) Zones   **(b)** Interfaces and elements

Fig. 3. BOT ontology
Source: `https://w3c-lbd-cg.github.io/bot/`

BOT is meant as an extensible baseline for use along with more domain specific ontologies following general W3C principles of encouraging reuse and keeping the schema no more complex than necessary. The W3C Linked Building Data Community Group has already extended BOT by various building elements like wall, window, and door, by furniture like chair and table, and by various mechanical, electrical and plumbing elements, see `https://github.com/w3c-lbd-cg/product`.

In our project, we added an extension for general factory elements to be able to represent all kinds of structures found in a factory, like production lines, modules, tools, etc.

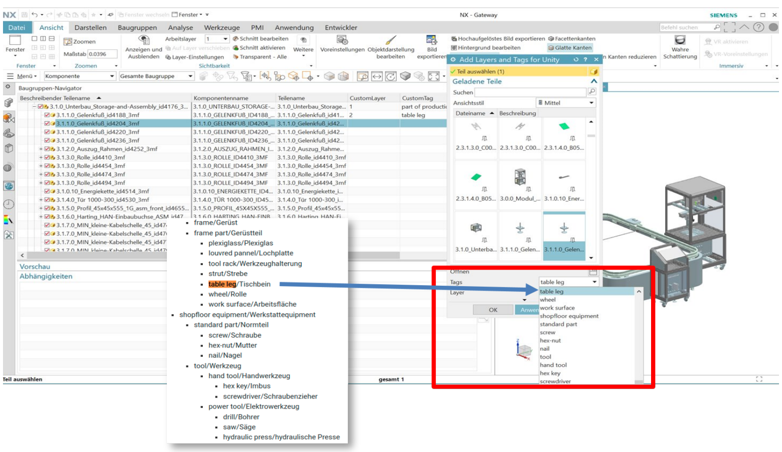


Fig. 4. Siemens NX with SKOS hierarchy

Since these factory elements are specific for a factory, quite diverse and dynamic, we simply introduced a means to tag all of these elements with a SKOS [12] hierarchy, and also extended various tools from the Digital Twin tool chain to allow the user to add, edit, and view these tags for all factory elements, see Fig. 4. Further extensions for factory elements include several properties for spatial relations, like `factory:disjoint`, `factory:intersects`, and `factory:within`, and also *zoom levels*. These global *zoom levels* allow to restrict queries to factory elements which are at a pre-defined zoom level, e.g., for selecting only factory elements which are obstructions for a robot.

The use of *zoom levels* here borrows from the term *semantic zoom* from the field of information visualization [23]. The most prominent example for this is the zoom feature of Google Maps: Not only the scale of objects increases when you zoom in, but completely new information (such as bus stops) is added. Similarly, the *zoom levels* in our Digital Twin allow to provide or hide information according to the requirements of the application: The same object (e.g., a manual working station) can be an obstacle to avoid for the navigation component of the robot, while at the same time it is a workplace for the human worker that can be augmented by an assistance system.

```
inst:go49508            a     factory:FactoryElement ;
        rdfs:label            "I40-Demonstrator" ;
        factory:tag           inst:tag_demonstrator ;
        factory:zoom          "1" ;
        bot:hasSimple3DModel  "UBOX(-1.13291454 1.418053 7.068856,
                                    4.66982937 2.85783315 12.8742294)" ;
        factory:disjoint      inst:go-1560 , inst:go-1376 , inst:go42888 ;
        factory:intersects    inst:go81898 ;
        bot:hasSubElement     inst:go23534 , ... , inst:go-1242 .
inst:tag_demonstrator   a     skos:Concept ;
        rdfs:label            "demonstrator" ;
        skos:broader ... .
```

This triple store with the semantic environment model is accessed by various software modules like robot planning and intention recognition via SPARQL queries [9] and SPARQL protocol [6]. The current SPARQL query language (version 1.1) supports property paths and thus can deal with reflexive and transitive closures of properties like `bot:hasSubElement` and `skos:broader`, so there is no need for a triple store directly supporting inferences, see the use of the unary operators + and * in the following SPARQL query snipped which finds factory elements which are located in the a demonstrator (named I40) and are tagged with tools.

```
SELECT ?fe ?label ?tag
WHERE {
    [] a factory:FactoryElement ;
        rdfs:label "I40-Demonstrator" ;
        bot:hasSubElement+ ?fe .
    ?fe a factory:FactoryElement ;
        rdfs:label ?label ;
        factory:tag ?tag .
    ?tag skos:broader* inst:tag_tool .
}
```

In case SPARQL queries are not enough, triple stores that support user-defined inferences can be used, which then facilitate advanced functionalities such as automatically inferring facts like `on(screwdriver, table)` from base spatial relations, which are important for robot action planning.

One such triple store is RDFox,[1] which supports Datalog using triples in the form `[s,p,o]` and also SPARQL expressions, so rules like the following are possible: `[?p, :hasChild, ?c] :- [?c, :hasParent, ?p] .`

[1] https://docs.oxfordsemantic.tech/

The following sketch of an RDFox rule can thus infer `on(tool, table)` by checking if a tool spatially intersects with a table and has a higher height than the table:

```
[?tool, :on, ?table] :-
    [?tool, :tag, :Tool],
    [?tool, :has3DModel, ?tool3DModel],
    [?tool3DModel, :center, ?toolCenter],
    [?toolCenter, :y, ?toolHeight],
    [?table, :tag, :Table], ...,
    [?tableCenter, :y, ?tableHeight],
    [?table, :intersects, :tool],
    FILTER(?toolHeight > ?tableHeight) .
```

Most triple stores support user-defined rules in similar forms, but with slightly different semantics. E.g., GraphDB supports rules similar to R-entailment [34], which extends RDFS [8] and is compatible to a significant subset of OWL [11].

Just like using ontologies to guarantee a common understanding of the Digital Twin, the declarative nature of rule languages again improves the ease of use of Digital Twins, compared to using imperative programming.

6. Implementation and Evaluation

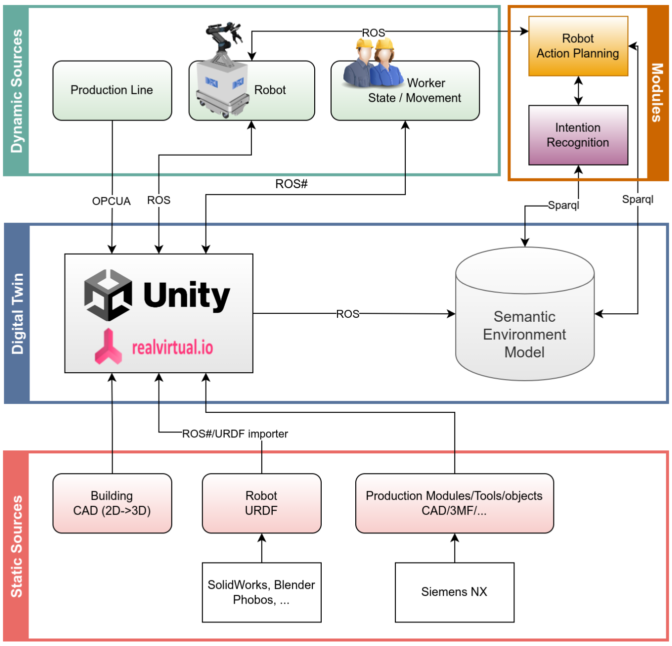


Fig. 5. System architecture of our implemented system

Fig. 5 depicts our implemented system architecture. We used Unity together with realvirtual.io,[2] as our framework for Digital Twins, which is accompanied by a triple store (currently, Ontotext GraphDB[3]) that contains the semantic environment, i.e., the relevant parts of the Digital Twin transformed to our extended BOT ontology.

The CAD models for the production modules are created with Siemens NX,[4] see Fig. 4. This tool has been extended to support semantic annotations, i.e., tags from a SKOS hierarchy

[2] `https://unity.com/ https://realvirtual.io/`
[3] `https://www.ontotext.com/products/graphdb/`
[4] `https://www.plm.automation.siemens.com/global/de/products/nx/`

Fig. 6. Unity displaying SKOS hierarchy and zoom layers.

and global zoom levels, and these annotations can then be imported in Unity as part of the CAD model, see Fig. 6.

Apart from this static initialization of the Digital Twin from the production environment, we mainly have to deal with dynamic updates for robot movement, and where tools and other dynamic objects like workpieces are. OPC Unified Architecture (OPC UA) is a machine-to-machine communication protocol used for industrial automation and developed by the OPC Foundation.[5] Since the production modules in our test-bed lab use OPC UA as controlling protocol, OPC UA clients were implemented in Unity. These OPC UA clients use the Pub/Sub concept to get dynamic changes (such as machine status) at real-time in the production module and update the Digital Twin.

In the developed system, ROS (Robot Operating System)[6] was generally used as an interface between different software components, such as robot and 3D environment. Each part of the proposed system is able to publish its current information to a corresponding ROS topic. For instance, the worker's position is tracked and published into the proper topic. In order to visualize the published information in the ROS topics and update the affected objects in the 3D environment, corresponding ROS subscribers (*agents*) were implemented using ROS# [7] in Unity. ROS# is a set of open source software libraries and tools in C# for communicating with ROS from .NET applications, in particular Unity. The ROS messages are also propagated to the triple store in appropriate intervals to ensure the environment model is consistent at all times, including spatial relations.

Scenarios Using Ontology-Based Digital Twin

As mentioned in the above introductory sections, we have two scenarios: (1) the Smart Maintenance Scenario and (2) the Manual Assembly Scenario. We use these two scenarios to demonstrate the use of the ontology-based Digital Twin for human-robot collaboration.

We make use of the object detection model as shown in Fig. 7 to infer which actions the user is performing by understanding which objects the user is viewing and interacting with in the two scenarios [33]. The egocentric field-of-view is obtained from the head-mounted device camera. On these video frames the object detection is performed. Using these observations, the goal is to provide the user with the necessary assistance via the environment model. The semantic Digital Twin provides the necessary context belonging to the respective scenario. It also acts as a mediator between different software components. Each object that the user interacts with has a set of associated *affordances*. These *affordances* are a list of all actions possible with a given object. (The use of the term *affordance* here is consistent with Don Norman's definition in the

[5] `https://opcfoundation.org/`
[6] `https://www.ros.org/`
[7] `https://github.com/siemens/ros-sharp`

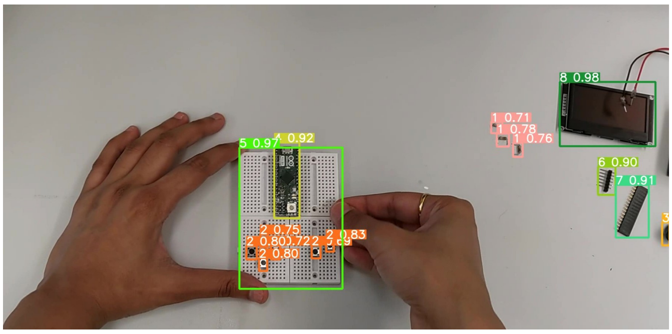


Fig. 7. Object detection for manual assembly scenario

field of human-computer interaction [21].) With this information at hand, context-specific robot assistance is provided. Also, this information can be used to show the worker relevant hints about how to interact with the objects.

Evaluation via Thought Experiment

Our evaluation is a thought experiment to evaluate our architecture with and without the ontology-based Digital Twin. Without the ontology-based Digital Twin, all software modules like robot action planning, object detection, and intention detection would communicate with the main components like the (real or simulated) robot only via ROS, i.e., get notified of changes of the environment via ROS messages. Each module would therefore have to deal with collecting the initial state and applying changes by itself, and inferring additional facts like spatial relations on its own. Apart from the additional burden of performing this multiple time within these modules, it is also likely that divergent conclusions would be drawn.

By using an ontology-based Digital Twin, all these conclusions are drawn at a single location, so every module has exactly the same view on the environment. Using a common ontology for this ensures that all modules have the same understanding of the environment, which otherwise would be hard to achieve. The declarative nature of SPARQL facilitates the communication between the modules and the Digital Twin.

7. Conclusion and Future Work

In this paper, we have described the concept and implementation of a semantic Digital Twin that serves as an information hub for all (human and machine) actors in the Smart Factory. It serves as a single point of truth for static as well as volatile information for them, reducing greatly the burden of one-to-one communication and updating and keeping consistent changes in states of sensor information etc. across the entire Smart Factory. By providing reasoning capabilities, e.g., about spatial relations, it also relieves all stakeholders of the duty to perform such reasoning by themselves. *Zoom levels* allow to provide applications such as assistance systems with environment information at exactly the granularity required for that particular application. A Unity visualization of the Digital Twin can serve as a basis for further assistance, e.g., for displaying an object's *affordances* to the worker.

Future work includes linking the Digital Twin to the Digital Product Passport of the product that is being assembled. The Digital Product Passport is a concept that is being developed to facilitate information exchange among various stakeholders along a product's lifecycle, e.g., between manufacturers and recyclers [24, 25, 13]. Information from the Digital Twin that could inform a Digital Product Passport includes time and place of production, the materials and parts used in the assembly, and joining or binder techniques used. This information may, for instance, be of great value for the disassembly process at the product's end of life. The *affordances* associated with a product may, in contrast, be of interest for potential users and could be provided as a kind of *interactive manual* via the Digital Product Passport.

Acknowledgments

The project InCoRAP is supported by the German Federal Ministry of Education and Research under grant no. 01IW19002.

References

1. S. R. Bader. *Semantic Digital Twins in the Industrial Internet of Things*. PhD thesis, Rheinische Friedrich-Wilhelms-Universität Bonn, June 2022.
2. Q. Bao, G. Zhao, Y. Yu, S. Dai, and W. Wang. Ontology-based modeling of part digital twin oriented to assembly. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 236(1–2):16–28, 2022.
3. A. Borrmann, M. König, C. Koch, and J. Beetz. Building information modeling: Why? what? how? In A. Borrmann, M. König, C. Koch, and J. Beetz, editors, *Building Information Modeling: Technology Foundations and Industry Practice*, pages 1–24. Springer International Publishing, Cham, 2018.
4. G. d. M. Costa, M. R. Petry, and A. P. Moreira. Augmented reality for human-robot collaboration and cooperation in industrial applications: A systematic literature review. *Sensors*, 22(7):2725, 2022.
5. J. A. Erkoyuncu, I. F. del Amo, D. Ariansyah, D. Bulka, R. Vrabič, and R. Roy. A design framework for adaptive digital twins. *CIRP Annals*, 69(1):145–148, 2020.
6. L. Feigenbaum, G. T. Williams, K. G. Clark, and E. Torres. SPARQL 1.1 protocol. W3C Recommendation, `https://www.w3.org/TR/2013/REC-sparql11-protocol-20130321/`, Mar. 2013.
7. M. Grieves. Origins of the digital twin concept, Aug. 2016.
8. R. Guha and D. Brickley. RDF schema 1.1. W3C Recommendation, `http://www.w3.org/TR/2014/REC-rdf-schema-20140225/`, Feb. 2014.
9. S. Harris and A. Seaborne. SPARQL 1.1 query language. W3C Recommendation, `https://www.w3.org/TR/2013/REC-sparql11-query-20130321/`, Mar. 2013.
10. R. Hercik, R. Byrtus, R. Jaros, and J. Koziorek. Implementation of autonomous mobile robot in smartfactory. *Applied Sciences*, 12(17), 2022.
11. P. Hitzler, M. Krötzsch, B. Parsia, P. F. Patel-Schneider, and S. Rudolph. OWL 2 web ontology language primer. W3C Recommendation, `https://www.w3.org/TR/owl2-primer/`, October 2009.
12. A. Isaac and E. Summers. SKOS simple knowledge organization system primer. W3C Recommendation, `https://www.w3.org/TR/skos-primer/`, Aug. 2009.
13. M. Jansen, T. Meisen, C. Plociennik, H. Berg, A. Pomp, and W. Windholz. Stop guessing in the dark: Identified requirements for digital product passport systems. *Systems*, 11(3), 2023.
14. G. Klyne and J. J. Carroll. Resource description framework (RDF): Concepts and abstract syntax. W3C Recommendation, `http://www.w3.org/TR/2004/REC-rdf-concepts-20040210/`, 2004.
15. M. Kümpel, C. A. Mueller, and M. Beetz. Semantic digital twins for retail logistics. In M. Freitag, H. Kotzab, and N. Megow, editors, *Dynamics in Logistics: Twenty-Five Years of Interdisciplinary Logistics Research in Bremen, Germany*, pages 129–153. Springer International Publishing, Cham, 2021.
16. B. Li, B.-c. Hou, W.-t. Yu, X.-b. Lu, and C.-w. Yang. Applications of artificial intel-

ligence in intelligent manufacturing: a review. *Frontiers of Information Technology & Electronic Engineering*, 18:86–96, Jan. 2017.

17. A. Malta, M. Mendes, and T. Farinha. Augmented reality maintenance assistant using yolov5. *Applied Sciences*, 11(11):4758, 2021.
18. A. M. Miller, R. Alvarez, and N. Hartman. Towards an extended model-based definition for the digital twin. *Computer-Aided Design and Applications*, 15(6):880–891, 2018.
19. P. Moder, H. Ehm, and E. Jofer. A holistic digital twin based on semantic web technologies to accelerate digitalization. In S. Keil, R. Lasch, F. Lindner, and J. Lohmer, editors, *Digital Transformation in Semiconductor Manufacturing*, pages 3–13, Cham, 2020. Springer International Publishing.
20. K. Nagorny, P. Monteiro, J. Barata, and A. Colombo. Big data analysis in smart manufacturing: A review. *International Journal of Communications, Network and System Sciences*, 10:31–58, Mar. 2017.
21. D. A. Norman. Affordance, conventions, and design. *Interactions*, 6(3):38–43, may 1999.
22. L. Orsag, T. Stipancic, and L. Koren. Towards a safe human-robot collaboration using information on human worker activity. *Sensors*, 23(3), 2023.
23. K. Perlin and D. Fox. Pad: An alternative approach to the computer interface. In *Proceedings of the 20th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH '93, page 57–64, New York, NY, USA, 1993. Association for Computing Machinery.
24. C. Plociennik, M. Pourjafarian, A. Nazeri, et al. Towards a Digital Lifecycle Passport for the Circular Economy. *Procedia CIRP*, 105:122–127, 2022. The 29th CIRP Conference on Life Cycle Engineering, April 4 – 6, 2022, Leuven, Belgium.
25. C. Plociennik, M. Pourjafarian, S. Saleh, et al. Requirements for a Digital Product Passport to Boost the Circular Economy. In D. Demmler, D. Krupka, and H. Federrath, editors, *INFORMATIK 2022*, pages 1485–1494. Gesellschaft für Informatik, Bonn, 2022.
26. J. Ploennigs, K. Semertzidis, F. Lorenzi, and N. Mihindukulasooriya. Scaling knowledge graphs for automating ai of digital twins. In U. Sattler, A. Hogan, M. Keet, et al., editors, *The Semantic Web – ISWC 2022*, pages 810–826, Cham, 2022. Springer International Publishing.
27. Y. Qu, X. Ming, Z. Liu, X. Zhang, and Z. Hou. Smart manufacturing systems: state of the art and future trends. *The International Journal of Advanced Manufacturing Technology*, 103, Aug. 2019.
28. M. H. Rasmussen, M. Lefrançois, G. F. Schneider, and P. Pauwels. BOT: the building topology ontology of the W3C linked building data group. *Semantic Web Journal*, 2020.
29. A. D. Rubio and J. de Lara. Semantic digital twins for organizational development. In *Second International Workshop on Semantic Digital Twins*, 2021.
30. M. Ruskowski, A. Herget, J. Hermann, W. Motsch, P. Pahlevannejad, et al. Production Bots für Production Level 4. In *atp magazin*, Sept. 2020.
31. B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack. Shaping the digital twin for design and production engineering. *CIRP annals*, 66(1):141–144, 2017.
32. C. Steinmetz, A. Rettberg, F. Ribeiro, G. Schroeder, and C. Pereira. Internet of things ontology for digital twin in cyber physical systems. In *2018 VIII Brazilian Symposium on Computing Systems Engineering (SBESC)*, pages 154–159, Nov. 2018.
33. H. Tavakoli, S. Walunj, P. Pahlevannejad, C. Plociennik, and M. Ruskowski. Small object detection for near real-time egocentric perception in a manual assembly scenario. In *EPIC@CVPR2021 workshop*, 2021.
34. H. J. ter Horst. Combining RDF and part of OWL with rules: Semantics, decidability, complexity. In *International Workshop on the Semantic Web*, 2005.