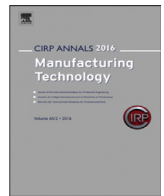




Contents lists available at ScienceDirect

CIRP Annals - Manufacturing Technology

journal homepage: <https://www.editorialmanager.com/CIRP/default.aspx>

Potentials and technical implications of tag based and AI enabled optical real-time location systems (RTLS) for manufacturing use cases

Sebastian Thiede (2)^{a,*}, Poorya Ghafoorpoor^a, Brendan P. Sullivan^a, Sebastian Bienia^b, Michael Demes^b, Klaus Dröder (2)^b

^a Chair of Manufacturing Systems, Department of Design, Production and Management, University of Twente, Enschede, the Netherlands

^b Institute of Machine Tools and Production Technology (IWF), Technische Universität Braunschweig, Germany

ARTICLE INFO

Article history:
Available online xxx

Keywords:
Manufacturing system
Object recognition
Real-time locating systems

ABSTRACT

Utilizing real-time position information of individual factory objects is a promising field of action in manufacturing systems. For realizing that, different types of real-time locating systems (RTLS) are available which differ according their inherent characteristics, performance and, thus, their feasibility for value adding manufacturing use cases. The paper introduces an innovative RTLS which utilizes optical AI enhanced sensors to detect and track objects. Detailed technical analyses also in comparison with established tag based ultra-wideband (UWB) RTLS underline the general feasibility and good performance. Finally, the capability profiles of those different RTLS technologies were brought together with the requirements of specific manufacturing use cases in order to derive favourable application fields.

© 2022 CIRP. Published by Elsevier Ltd. All rights reserved.

1. Introduction

Digitalization in manufacturing - often associated with terms like Industry 4.0, smart manufacturing or industrial internet of things (IIoT) - involves a diversity of digital technologies and methods that connect production entities and generate large amounts as well as new types of data [1]. In combination with appropriate data processing and virtual models, the development of innovative applications for design and operation of manufacturing is enabled to eventually improve, e.g. productivity, flexibility or sustainability [2]. In this context, also innovative sensors play an important role since they provide advanced insights into manufacturing processes or systems and are getting more and more economically feasible. As one example for that, real-time information about the position of individual and potentially moving factory objects became an interesting field of action in the last years [3]. Under the term Real-Time Locating/Location Systems (RTLS, paper will use this term) or Indoor Positioning Systems (IPS), this could include different types of factory entities such as materials, production orders, logistic elements, machines, tools or persons [3]. The basic principle is shown in Fig. 1: for identifying and tracking objects different technologies are available (e.g. tag based) that typically make use of infrastructure installed RTLS hardware (e.g. communication anchors). Processed location data of individual objects is used in digital models that enable a wide range of use cases (overview in [3]), e.g. tracking and booking of orders, counting of persons in emergency situations, prevention of accidents, indoor navigation or monitoring of quality related timing/zoning (e.g. cold chain).

* Corresponding author.
E-mail address: s.thiede@utwente.nl (S. Thiede).

<https://doi.org/10.1016/j.cirp.2022.04.023>

0007-8506/© 2022 CIRP. Published by Elsevier Ltd. All rights reserved.

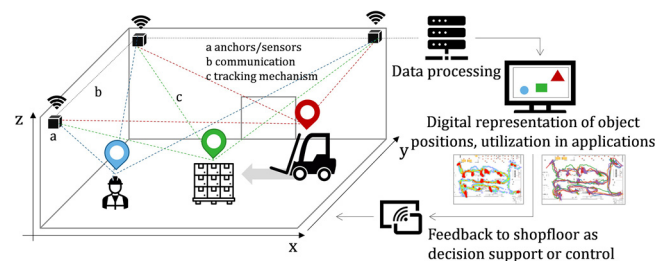


Fig. 1. General principle of RTLS in factories.

Tag based approaches (e.g. using Radio-Frequency Identification/RFID or Ultra-wideband/UWB) are the most established RTLS in manufacturing (and beyond, e.g. in sports, healthcare) and various applications can be found in research and industrial practice [4,5]. But in the end, each use case is connected with specific requirements, e.g. in terms of objectives (what shall actually be improved?), related factory objects and stakeholders as well as boundary conditions (e.g. size and complexity of environment). This might lead to differing favorable RTLS technologies or implementation options, e.g. regarding tracking principle, anchor/sensor quantity and layout, communication standard and architecture as well as type and resolution of data.

Against this background, this paper introduces an innovative optical RTLS (ORTLS) approach and investigates the feasibility, benefits but also challenges for manufacturing use cases. Detailed technical investigations for both established tag based (UWB) RTLS and optical RTLS are carried out to derive differences and potentials as well as limits. This is finally brought together with requirements of selected use cases in order to identify possible application fields for both types of RTLS.

2. Technical background and research demand

Various technological principles are used for RTLS, comprehensive overviews can be found in [4–6]. This paper focuses on tag based RTLS (most established in manufacturing) and optical RTLS (background of presented innovative approach).

2.1. Tag based RTLS

Tag based RTLS make use of Radio Frequencies (RF) to determine the relative location of a tracked object (equipped with an active or passive tag) with respect to multiple so-called ‘anchors’ within a grid. Available systems nowadays typically base on Wi-Fi, UWB, BLE (Bluetooth Low Energy), RFID, Global Positioning System (GPS), or a combination. To provide a reliable localisation of the tags within the environment, anchors are installed at defined locations and the tag can ideally receive strong signals from several anchors for tracking. Tags are available in different variants (e.g. in terms of geometry, power supply) and can be attached to any factory object. Signal data of tags/anchor combinations is converted into (typical 2D) position information of objects. Available tag based RTLS differ regarding the type of tags and anchors, communication protocols but also embedded algorithms for localization (e.g. Time of Arrival/ToA) [3,6].

2.2. Optical RTLS

Also optical principles can be used for position detection of objects [4]. Common approaches use optical sensors attached to the moving objects to determine their position based on detecting optical features in the environment (e.g. via SLAM algorithm). Just few approaches can be found that base on optical sensors installed in the environment for getting position information of objects within. Even more, current work is/ended in early development stages and/or is not related to manufacturing applications [7,8].

2.3. Research demand

RTLS are a growing topic in the last 10–20 years. Many publications on developing different fundamental principles can be found but mainly focus on specific RTLS technologies (e.g. just UWB or RFID). There are also comprehensive state of the art overviews [4,5] but those are not taking into account boundary conditions of factories. Manufacturing related RTLS literature is mostly focusing on the description of specific implementation use cases based on a selected technology. Recent work from Barbieri et al. [9,10] shows a more generalizable comparison of RTLS in manufacturing settings but purely focused on tag based (UWB) systems. Hence, there are limited contributions towards systematic investigations of benefits and drawbacks of different RTLS technologies for different use cases. Even more, tag based RTLS are well established but there are also some inherent characteristics (e.g. necessity of tags, robustness) that cause challenges (see Section 4) and impede broader application. Given that, this paper introduces an innovative optical RTLS (ORTLS) approach. While this ORTLS goes beyond established systems, one major research question is whether it is actually usable for manufacturing applications. But to overcome an isolated consideration of the new technology, systematic and comparable technical analysis of both optical RTLS (ORTLS) and established tag based RTLS (UWB) was conducted. Results help to identify technical potentials but also limits of both approaches. Based on that, recommendations regarding feasibility and favorability for different use cases can be derived.

3. Optical real-time location system

In contrast to tag based RTLS, the proposed optical real-time location system (ORTLS) is able to classify and localise various objects (e.g. persons, transport vehicles) on the basis of their optical properties. The optical localisation system consists of (multiple) AI sensors that are installed decentrally in the infrastructure. Fig. 2 shows a schematic representation of the functional components and the internal

workflow from data collection to processing of the position information on a central server. The AI sensors follow the edge computing paradigm and each consist of an image sensor and a computing unit. Based on raw optical data generated by the image sensor, an object recognition algorithm utilizing a convolutional neural network (CNN) is used. Through a pose detection model based on a Resnet18 backbone, individual object classes (e.g. person) and their specific key features are detected. Through a set of key features, a unique object stand-up point (and also orientation) can be derived by a model of the respective object class. The calculated stand-up points in the image plane of the AI sensors are then transformed into real coordinates of the industrial environment through perspective transformation. The real coordinates of each detected object are sent to a central application server via a communication interface. A Kalman filter algorithm is used on the central server to process the multi-channel sensor coverage (same objects are detected simultaneously by several sensors). In case of a short-term non-detection of objects (e.g. completely obscured object), the Kalman filter can be used to derive a continuity of the trajectories by motion predictions based on data histories. To support ORTLS planning and verify system functionality, a procedure for an automated analysis of the uncertainties is also available [11]. Through the edge computing approach and the usage of multiple AI sensors, a reasonable level of functionality can be maintained even in the event of a failure of individual sensors. The edge principle also enables an efficient scale up of the system and is favourable from data privacy point of view: image data is processed directly on the AI sensors and does not have to be sent or stored centrally. Only anonymous coordinates of a specific object class are sent for further processing and use of the position information.

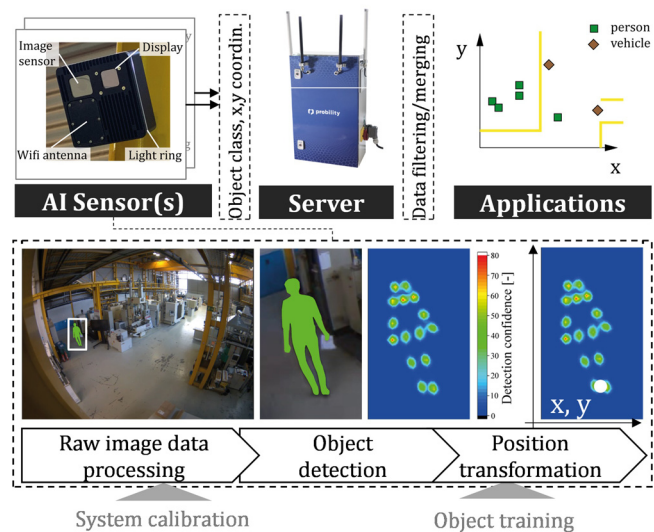


Fig. 2. Optical real-time locating system (ORTLS) functional principle.

4. Technical analysis of UWB RTLS and optical RTLS

4.1. Qualitative comparison of tag based and optical RTLS

Both tag based and optical RTLS can be used for gathering real-time position information of objects but the technological principles are very different. Those inherent specific characteristics lead to different potential benefits but also challenges for manufacturing applications. Table 1 gives a descriptive overview along different criteria (in extension of e.g. [3]). In summary, optical RTLS obviously do not need separate tags which inherently leads to potential benefits in terms of robustness (e.g. electromagnetic/communication disturbances or human errors), completeness of coverage and hardware efforts. On the other side, ORTLS need a line of sight, necessary training of objects to be detected and have potential limitations when it comes to small and similar looking objects. Data privacy is a potential concern for all RTLS, e.g. when it comes to detecting humans. Tag based

Table 1
RTLS characteristics in context of manufacturing applications.

	Tag based RTLS (UWB)	Optical RTLS
1. Hardware (also related to costs)	array of anchors and individual tags (with power supply) for each object	array of optical AI-Sensors, potential use of existing cameras, no tags
2. Identif. (ID) of specific objects	clear identification of specific/individual objects with distinct tag ID	object classes detected, potential limitations for individual objects
3. Object size	no restrictions as long as tag can be attached	potential limitations for small objects
4. Positioning accuracy	high accuracies subject to system setup, see Section 4.2	very high accuracies subject to system setup, see sect. 4.2
5. Comprehensive-ness of detection	tag necessarily needed, risk of missing or damaged tags	Inherently full coverage of objects in detection zone once trained
6. Robustness	potentially prone to technical disturbances and human errors (tags)	line of sight crucial, less prone to disturbances and human errors
7. Additional sensing	tags with further sensor capability (e.g. temperature)	no further sensing, multi-use of data possible
8. Data privacy	full and distinct traceability of objects, humans etc.	anonymized detection, opt. sensor sensitive topic

RTLS allows a full traceability of individuals via attached tags (as also used in sports) but can be removed. ORTLS just detects anonymous persons (whereas technically more is possible) but optical sensors might be perceived critically. Many of those more qualitative characteristics are inherently given by the functional principle. Specific technical aspects related to RTLS functionality (e.g. positioning accuracy) need additional investigation which will be described in the following section.

4.2. Experimental analyses

Provision of position data for different factory objects is a main function of RTLS. Thus, positioning accuracy is an important performance criterion. As indicated before, cross-technology RTLS performance measurements are rarely available for manufacturing settings and not at all for this innovative type of ORTLS. Thus, this paper provides a systematic experimental comparison of a commercial tag based RTLS (UWB technology with 6 respectively 4 anchors) and the new ORTLS (with detection of humans in this case, 4 sensors). One important aspect is that RTLS performance might be depending on the system type, case specific implementation and existing boundary conditions. To ensure comparability, a systematic experimental procedure was defined and both RTLS were set up and analysed in the same, clearly defined and controllable manufacturing related environment with limited disturbances. To enable validation, the environment was measured and a physical grid (with 32 1.0×1.0 m zones) was defined. Therewith, comparable circumstances are ensured. The impact of different influencing factors was investigated through systematic, stepwise variation (e.g. system setups, coverage line of sight).

4.2.1. Stationary positioning tests

The first series of experiments focused on reproducibility of positioning information in a stationary setting, meaning the object under investigation did not move. Fig. 3(a) illustrates the representative results obtained from a series of measurements. The center of each grid zone was always the real physical position of the object and was determined through measurements prior to the start of experimentation (black point, average deviation – red point). Based on that, several experiments were carried out with both RTLS types and also different system configurations (CFG) in order to identify influencing factors. Fig. 3(b) gives an overview of the results in terms of deviations from the actual position (in m). Three configurations (CFG) of tag based RTLS are included with different anchor communication scheme (CFG1: 6 wired anchors, CFG2: wireless) and reduced number of anchors (CFG3: 4 anchors). To underline the variability of data but also the technical feasibility for an ideal setup, values for all zones but also for the 10 best zones (individual selection per RTLS type) are shown. Several relevant insights can be taken away from here. The average deviation for the tag based RTLS is around 0.28–0.38 m (with higher values for CFG2 and CFG3) over the whole grid but actually just 0.13–0.17 m for the best 10 zones which are typically in the center of the considered area (as also visible in Fig. 3). Thus, acceptable accuracies are possible but depending on the specific RTLS setup

with good coverage of the area of interest. ORTLS related experiments lead to an average accuracy of 0.14 m for the whole grid and 0.05 m for the best zones. Additionally, significantly less variation can be observed. However, a spatial influence is given as well with best results in the center area of the (triangular) cone of sight of the optical sensors. Altogether, when it comes to accuracy ORTLS can be seen as feasible and potentially even more accurate alternative to tag based RTLS. However, the type of object under investigation needs to be trained for proper detection and inherently a sufficient line of sight is necessary. For tag based RTLS the influence of limited line of sight was investigated through covering the tag with different materials. It turns out that cardboard and plastic have limited influence but metal coverage lead to factor 2–3 worse accuracy due to changing signal properties. This gives important hints for operational scenarios and feasible areas for attaching tags on objects.

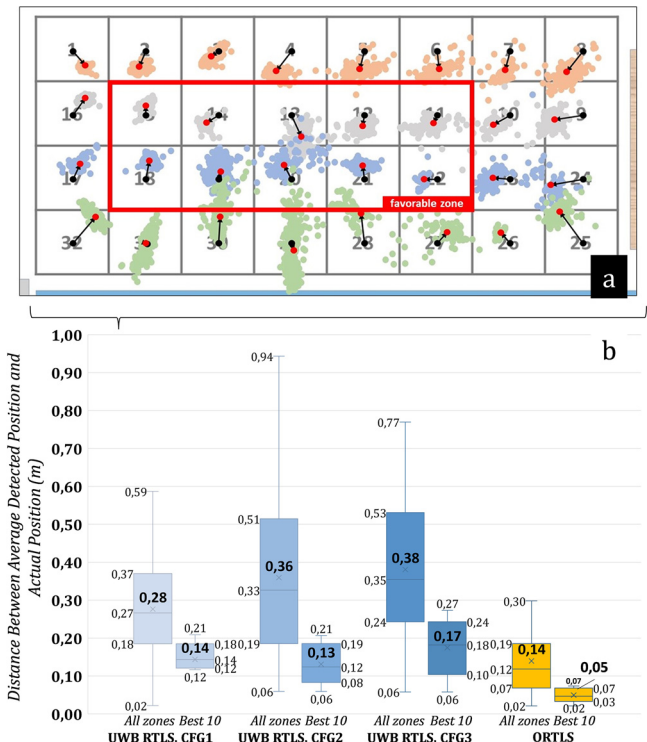


Fig. 3. Results of stationary experiments with different RTLS.

4.2.2. Dynamic positioning tests

For many manufacturing use cases, stationary accuracy is not sufficient while motion plays an important role. This influence was also analysed for both types of RTLS. Fig. 4(a) shows exemplary results and occurring deviations around the real pathway. Experiments for varying motion speed (0.3–1.5 m/s) along a defined straight path were conducted, Fig. 4(b) shows the respective results based on CFG1 (identified as best in stationary setting). The experiments took place in the best covered area so resulting values need to be compared to the previously introduced best zones results. Interestingly, while the variation of values got larger, accuracy is in average still in the same order of magnitude for both RTLS types (with ORTLS still being 50% more accurate). The variation of speed has also no significant influence here. Altogether, motion has clearly an impact on the robustness of results which actually may cause challenges in sensitive use cases. But in average both RTLS still show a good performance.

5. Implications for use case definition

The technical analysis underlined the different profiles of UWB RTLS and ORTLS - both technologies are in general capable to be used in manufacturing. But as already introduced in Section 1, feasibility and favourability depends on requirements and boundary conditions of the specific use case. Cost-utility analysis is a possibility to come to

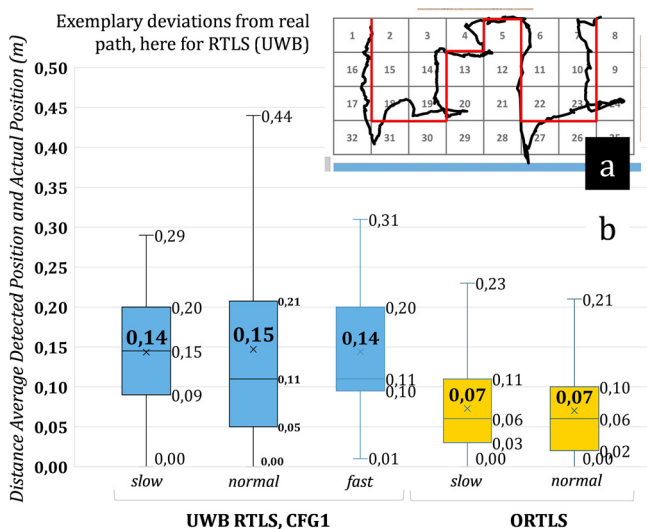


Fig. 4. Results of dynamic experiments with different RTLS.

a meaningful technology decision. Fig. 5 shows a simplified example for selected RTLS use cases. The requirements are summarized based on criteria from Table 1 and are being exemplary weighted (could be supported with e.g. pairwise comparison) depending on relevance for each use case. Requirement fulfilment is assessed through experts and reflects the experimental analysis. The resulting weighted sum gives an indication of the favourability of either tag based or optical RTLS. Obviously both weighting and technology assessment need to be case specific but this more generalized overview gives already some indications. ORTLS can be an interesting alternative when it comes to the accurate, robust and complete detection of defined types of objects (e.g. all humans in an area) in cost sensitive settings. Tag based RTLS are preferable in cases of necessary distinct identification and tracing of individual objects (of different types/sizes) or even direct interaction (e.g. in case of navigation). Also combinations of both technologies are possible.

Manufacturing use cases	Use case requirements (numbers referring to criteria from Table 1)						RTLS
	specific object identification (size & ID, 2/3)		accuracy requirements (4)	cost sensitivity / return of investment (1)	comprehensiveness (5) & robustness (6)		
Tracking/booking of orders or tools	50%	4 2	15% 3 4	20% 2 3	15%	3 2	UWB RTLS - 3.3 ORTLS - 2.5
Accident prevention (e.g. forklift/ human)	5%	4 2	20% 3 4	20% 2 3	50%	2 4	UWB RTLS - 2.2 ORTLS - 3.5
People counting (e.g. emergency case)	5%	4 2	5% 3 4	30% 2 3	60%	1 4	UWB RTLS - 1.6 ORTLS - 3.6
Indoor navigation of humans or AGV	50%	4 2	30% 3 4	10% 2 3	10%	4 4	UWB RTLS - 3.5 ORTLS - 2.9
Automated material flow analysis	20%	4 2	20% 3 4	50% 2 3	10%	2 3	UWB RTLS - 2.6 ORTLS - 3.0

Legend: Weight RTLS (UWB) ORTLS fulfilment assessment: rating from 1 (very low) to 4 (very high)

Fig. 5. Cost-utility analysis for RTLS selection in exemplary use cases.

To explain the case specific reasoning for selecting appropriate RTLS, Fig. 6 shows an exemplary use case. It deals with the prevention of accidents with material handling equipment (here forklift trucks) and persons in production environments. This is actually still a major challenge for safety in factories with over 36.000 notifiable accidents per year just in Germany [12]. As already indicated in Fig. 5, comprehensiveness (all relevant objects need to be detected but not all might have a tag) and robustness (large factory settings with many potential disturbances), good accuracy also in dynamic situations (moving objects) and a cost efficient setup (no direct payback/monetary added value) are crucial criteria. Given that, ORTLS is a feasible option here and was actually implemented in this case. As shown in Fig. 6, persons and forklift trucks are detected by a network of optical sensors and upcoming critical situations are estimated. The forklift truck driver is informed in real-time through a warning signal and/or potentially the vehicle can be automatically slowed down.

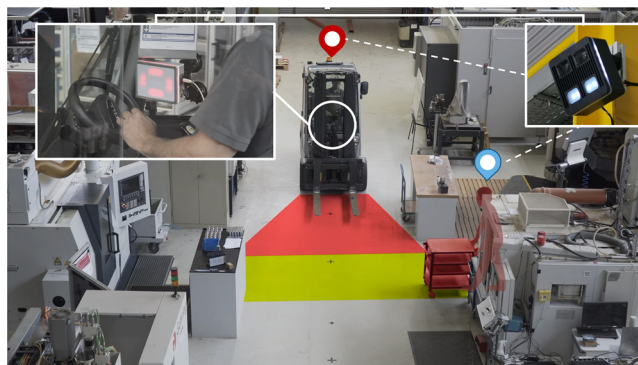


Fig. 6. Exemplary safety related use case with ORTLS implementation.

6. Summary and outlook

The paper introduces an innovative RTLS which utilises optical AI sensors to detect and track objects in factories. Detailed technical analyses underline the general feasibility and good performance as well as differing characteristics compared to established tag based UWB systems. The capability profiles of different RTLS technologies were brought together with the requirements of specific manufacturing use cases in order to derive favourable application fields. For ensuring proper validation as well as generalisability and comparability between different RTLS, a controllable manufacturing environment was defined for the experiments. Further work will focus on transferring those results to larger scale factory cases with more disturbances. Additionally, ORTLS performance, robustness and functionalities also in light of other potential use cases will be improved.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors thank the European Institute of Innovation and Technology (EIT) for funding the Cross-EIT project SAIFE (“Safety testbeds through AI for food production environment”).

References

- [1] Kang HS, Lee JY, Choi S, Kim H, Park JH, Son JY, Kim BH, Do Noh S (2016) Smart Manufacturing: Past Research, Present Findings, and Future Directions. *International Journal of Precision Engineering and Manufacturing* 3(1):111–128.
- [2] Schuh, G, Anderl, R, Dumitrescu, R, Krüger, A, Ten Hompel, M. (2020). Industrie 4.0 maturity index: Managing the digital transformation of companies, acatech study.
- [3] Thiede S, Sullivan B, Damgrave R, Lutters E (2021) Real-Time Locating Systems (RTLS) in Future Factories: Technology Review, Morphology and Application Potentials. *Procedia CIRP* 104:671–676.
- [4] Mautz R (2012) *Indoor Positioning Technologies*, Habilitation ETH Zurich.
- [5] Brena Ramon F, García-Vázquez Juan Pablo, Galván-Tejada Carlos E, Muñoz-Rodríguez David, Vargas-Rosales Cesar, Fangmeyer James (2017) Evolution of Indoor Positioning Technologies: A Survey. *Journal of Sensors*. Article ID 2630413. <https://doi.org/10.1155/2017/2630413>.
- [6] Zafari F, Gkelias A, Leung KK (2019) A Survey of Indoor Localization Systems and Technologies. *IEEE Communications Surveys Tutorials* 21(3):2568–2599.
- [7] Krumm J, Harris S, Meyers B, Brumitt B, Hale M, Shafer S (2000) Multi-Camera Multi-Person Tracking for EasyLiving. In: *Proceedings of the 3rd IEEE Workshop Visual Surveillance*, 3–10.
- [8] Lee YJ, Park MW (2019) 3D Tracking of Multiple Onsite Workers Based on Stereo Vision. *Automation in Construction* 98:146–159.
- [9] Barbieri L, Brambilla M, Trabattoni A, Mervic S, Nicoli M (2021) UWB Localization in a Smart Factory: Augmentation Methods and Experimental Assessment. *IEEE Transactions on Instrumentation and Measurement* 70:1–18.
- [10] Karaagac A, Haxhibeqiri J, Ridolfi M, Joseph W, Moerman I, Hoebeke J (2017) Evaluation of Accurate Indoor Localization Systems in Industrial Environments. In: *Proceedings of the 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, IEEE, 1–8.
- [11] Bienia S, Demes M, Dreger J, Dröder K, Thiede S (2022) Functional Analysis of an Optical Real Time Locating System in Production Environments accepted for publication at In: *Proceedings of the 55th CIRP Conference on Manufacturing Systems*, Lugano.
- [12] DGUV (2020), Arbeitsunfallgeschehen 2020, <https://publikationen.dguv.de>.