Beszámoló

Magyar Állami Eötvös Ösztöndíj

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Szakmai teljesülések, kutatások előrehaladása

A mobilitás céljaként kitűzött szakmai kapcsolatok erősítése sikeresen teljesült, amelynek eredményeként jelenleg is közösen dolgozunk nemzetközi pályázati anyagok benyújtásán a két intézmény vezetésével.

A Digitális Iker fejlesztése kapcsán Manuel Müllerre a fogadó intézmény PhD hallgatójával elkészítettük a „Self-improving situation-awareness for human-robot-collaboration using intelligent Digital Twin” (1. számú melléklet) című kéziratunkat, amelyben társszerzőként vettem részt. A kézirat hamarosan (véglegesítés alatt) benyújtásra kerül a Spreinger „Journal of Intelligent Manufacturing” Q1-es folyóiratba.

A robosztus helymeghatározási rendszer fejlesztése kapcsán jelentős előrelépéseket tettünk. Megalakult a nemzetközi pályázathoz szükséges konzorcium és jun-prof. Andrey Morozov vezetésével elkezdtük előkészíteni a pályázati anyagot (2. számú melléklet).

Részt vettem a *27th International Conference on Emerging Technologies and Factory Automation, ETFA 2022* konferencián nem csak előadóként (3. számú melléklet), hanem két „Special Session” szervezőjeként is. A konferencia kapcsán elfogadásra került konferencia cikkünk is (4. számú melléklet).

Köszönhetően a Tempus Közalapítvány által megítélt Magyar Állami Eötvös Ösztöndíjnak jelentősen növelhettem a nemzetközi kapcsolatrendszeremet és megjelenésemet, továbbá személyesen is találkozhattam és dolgozhattam az Operátor 4.0 kutatói hálózatom kiemelkedő tagjaival. A hamarosan benyújtandó folyóirat cikkünk és a már elfogadott konferencia cikkünk elősegíti szakmai és kutatói életpályámat.

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Self-improving situation-awareness for human-robot-collaboration using intelligent Digital Twin

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Abstract

The situation-awareness, particularly of the collaborative robot plays a crucial role when men and machine work together in a human-centered, dynamic environment. Only if the human understands how good the robot is aware of its environment, they can build trust and hand over tasks the robot is able to complete successfully. However, this state of situation-awareness is not yet described for collaborative robots. Moreover, the process of improving situation-awareness is up to now only described for humans, but not for robots. In this paper, the authors propose a metric for measuring the state of situation-awareness. Moreover, the scheme of situation-awareness is adapted to the domain of collaborative robots to systematically improve on the situation-consistency. The proposed metric and the improvement process of the situation-consciousness are evaluated using the mobile robot platform *Robotino*. The quality metrics show reasonable behavior and due to the improvement process, the consistency.

Keywords: keyword1, Keyword2, Keyword3, Keyword4

1 Introduction

Close cooperation between humans and collaborative robots (Cobot) is envisioned to make future production particularly efficient by combining the strengths of humans and machines and compensating for their respective weaknesses. To achieve this, Cobot must master complex problems in changing environments. Accordingly, the models must also be continuously updated to adapt to the changing environment. In this way, the Cobot must learn to constantly re-assess situations and adapt behavior. However, this change has the potential of misunderstandings with the worker with whom the robot interacts. In fact, the main issue of the Cobot is the human factors, as the Cobot consider three main dimensions: robot features, modern production systems characteristics, and human factors [14]. Improving the situation-awareness of Cobot may affect the performance of the operators, as it may be a source of psychological stress for the operator. Operator 4.0

concept [29] focuses on the support of the human operators with the enabling technologies [31]. The Cognitive Operator 4.0 proposed a deep perception, awareness, and understanding between both collaborative agents [36]. The situation-awareness of the Cobot could be the next essential element of human-robot collaboration. A summary of the significant considerations related to Cobot acquisition and deployment is proposed in Ref. [5]. When discussing human-machine collaboration, we must discuss the humans feel about the automation system [4]. Furthermore, Kansei Robotics can help adapt robots to human-centered manufacturing. The Kansei factor could effectively keep a comfortable state thanks to the emotional synchronization in human-robot interaction [16]. Industry 5.0 defines three main pillars for Industry 5.0: (i) Sustainability, (ii) Resilience, and (iii) Human-centricity [7]. Operator 5.0 [28] aims to solve the last two issues. All these upcoming technologies heavily rely on models and the capability of making sense of them. It is therefore important to build an understanding of the robot's models and communicate these to the worker in order to create mutual understanding. This is particularly challenging because computer systems perceive the environment differently than humans and therefore sometimes draw different conclusions. A virtual representation is required to let the human workers dive into the insights the robot generates. As the need for cooperation between human and machine is particular important in the avionic and spacecraft domain, the NASA launched in 2012 the concept of the Digital Twin (DT), defined as "virtual representation of a physical asset"[2]. In the context of this work, this virtual representation includes modeling the environment of the system. Since its initiation in 2012, the concept of the Digital Twin has evolved. Obviously, the quality of the virtual representation depends directly on the quality of the models. The question of where to start and end modelling, however, is still a point of discussion. According to West and Blackburn 2018, this quality of models competes with effort. On the one hand, it is impractical or at least uneconomical to model every detail [38]. On the other hand, outdated or inaccurate models can lead to misinterpretation of a situation and thus to suboptimal or even dangerous patterns of action. At this point, the Digital Twin requires intelligence to manage its models autonomously and communicate them. To this end, the intelligent Digital Twin (iDT) [2] extends the concept of the Digital Twin to include aspects of intelligence such as data analyzing and reasoning. Situation consciousness, specifically environmental and self-consciousness comes into play. Consciousness depicts the level of understanding and therefore depicts the quality of awareness. Situation-consciousness depicts the quality of the ability to understand the environment and oneself. To understand the environment and oneself, a person or a system respectively has to reason about the own models. In consequence, a high situation-consciousness correlates with the recognition of model boundaries, synchrony of virtual and physical world (for humans this is the gap between imagination and reality), and identification and characterization of perturbation events.

The goal of this paper is to describe the cobot's awareness, particularly of itself and its environment, and to present methods for increasing this awareness. In the process, the following research questions (RQs) will be answered:

- RQ1: How can situation-awareness be measured?
- RQ2: How can a Cobot undergo the situation-awareness process of increasing situation-consciousness?
- RQ3: How can consciousness be communicated to a human worker using the Digital Twin?

The reminder of this article is organized as follows: The paper continues with the related works. Thereafter, the authors introduce the situation-consciousness to answer the first research question. Having introduced the situation-consciousness, the paper describes the process of building it. The subsequent section exemplarily shows the application of the situation-consciousness and its improvement with experiments. The paper closes with some conclusions.

2 Related Works

A humanities' perspective on consciousness and awareness. Consciousness is heavily discussed in humanities like neuroscience and psychology [35] as it describes the degree of understanding what happens with and around an individual. It is the way of judging the state of awareness. For humans, different approaches for measuring consciousness exist [17]. Roughly speeking, the methods for determining human's consciousness group to either ask the respondent to describe what he or she experienced (subjective method), or measure neural activity in the brain (objective method). Unfortunately, However, these measuring methods do not apply for Cobot and must be modified. To the best of the authors' knowledge the measurement of consciousness is missing for the technical domain such as Cobot. However, researchers studied situation-awareness in the technical domain since the 1990s.

Situation-awareness and its measurement in the technical domain. In the well-cited work by White (1991)[39], the author locates the situation assessment in level 2 of the JDL sensor fusion model. In this level, "knowledge about objects, their characteristics, their relationships with each other and their cross force relations are aggregated in an attempt to understand the current situation"[19]. In the same period, Endsley introduced a theory of situation-awareness for dynamic systems. In her studies, Endsley focuses on the awareness of the worker, not of the robot [40]. She established a three-step process defining the situation-awareness: Perception, Comprehension and Projection [12]. In [11], different methods of measuring human situation-awareness are presented. Unfortunately, ranging from indirect measures like performance measures to subjective ones like questionnaires, these techniques are hardly applicable to robots [8]. In the time range 2018 to 2022, picking the first 100 hits of the 481 publications listed in the web-of-science under the query of "title contains situation-awareness", only fife contribution papers in English language relate to the awareness of technical systems. To this end, the authors agree to the finding of [8] that many approaches use the term situation-awareness without giving any definition. Under the fife contribution papers, [41] argues for the usage of small and fast ontologies for fast decision-making in order to gain situation-awareness from ontologies in real-time. It underlines the importance of context for situation-awareness. The authors take up the idea of a set of small meta-models in measuring the quality of the context. [9] modify Endsley's scheme for seamless learning. In their attempt to understand the quality of the learned concepts, they describe a metric for the context-awareness quality, which is one major aspect of situation-awareness. The authors extend this idea in using an adapted Levenshtein distance instead of simply count the number of elements. [13] discusses information fusion with deep multimodal image fusion according to the JDL scheme and metrics to measure the fusion quality. They argue that different measures must be combined in order to describe situation-awareness quality. [43] apply the distributed situation-awareness model to teams of both human and automation. Focusing on perception and projection, they use Bayesian belief networks under limited information to reach situation-awareness. They describe a "relevance metric" which measures the accuracy of projection of a subset of agents and a "transition metric", which measures the quality of a predicted value. However, the metrics of both approaches are very specific for the respective deep learning approach and do not really apply for Cobots. In the domain of service Cobots, [34] propose an auto-regressive model for recognizing the level of interest towards an interaction with the robot. Focusing on the human-robot-interaction, the situation-awareness reflects the emotional state of the human it works with. They therefore define the user's level of interest to characterize the situation. The idea to include not only physical aspects but also non-physical aspect into account is taken up in the authors' situation-awareness model. However, the question of how to build an expectation of the intention of a human is out of focus of this paper. In fact, the work of [8] comes closest to this work. They transfer the concept of situation-awareness to autonomous agents propose to measure situation-awareness in terms of the opposite, namely surprise. The authors of this paper take up this idea in the measurement of the consistency and the measurement of the coverage. Moreover, [8] follow the same approach to formally define the situation-awareness to derive a protocol to improve it. However, in the authors' point of view, context and situation are different and therefore context-awareness and situation-awareness differ. Moreover, the concept of Dahn et al. builds on aspects, which they define as rules formulated in simple logical expressions that describe the environment. In contrast, the authors use states to describe the environment. This way of modelling allows for including uncertainties like tolerances in a more convenient way. Moreover, the authors disagree with the statement that situation-awareness is a binary property. If situation-awareness is below 100%, the authors agree that the system might fail surprisingly, since the one missing aspect makes the difference. More often, missing a relevant aspect will lead to a non-optimal but a usable solution nevertheless. For this reason, it makes sense to reason about the state of the awareness. On top of that, it is easier to improve a continuous quantity than a binary one.

The so-called real-time locating systems are already integrated into the Digital Twin, and the simulation behind that [30]. However, these methods still do not consider the situation-awareness of the automated systems. Finally, the framework of [8] does not really tell whether a system is situation-aware but rather that it is not. It is limited to the surprise but does not take into account parameters like precision, uncertainties in the processing of information etc. The digital twin and its simulation gap come into focus as a step toward real-world problems.

The Digital Twin and the Simulation Gap. Driven by the idea of fully simulatable aerospace missions, the NASA started the vision of the Digital Twin in 2012 [15]. The first approach painted the Digital Twin equipped with a set of models that cover every detail of the system. However, this approach showed several drawbacks rendering this approach unrealistic or at least uneconomic [38]. In consequence, the survey on the Digital Twin [23] hardly found full-featured Digital Twins. Nevertheless, this field progresses a lot, just with adapted strategy. Operational simulation becomes one core characteristic of the Digital Twin. The characteristic of synchronization puts a strong emphasize on the reality-to-simulation transfer keeping the cyber world consistently to the physical asset [2, 3]. More recent work considers the integration of intelligence to the Digital Twin [18]. Waving away the claim of modelling the asset perfectly accurate, the research on the simulation gap [25] comes into touch with the Digital Twin research. It also implies that the situation-awareness is at stake and cannot be assumed without further measures. Approaches exist that tune the simulator to narrow the simulation-to-reality gap [6], but do not yet solve the problem entirely. Following a different approach to bridge the simulation-to-reality gap, [45] identify the key aspects: system identification, domain randomization, domain adaption, and learning under disturbances. The core difference of the Digital Twin compared to former pure simulation is the direction of the transfer. Instead of transferring an initially build simulation to the reality, the Digital Twin runs operational simulation that have to be adapted to the perceived real world. To this end, [26] propose a method to close the reality-to-simulation gap. However, it does not tackle the question of situation-awareness and situation-consciousness. These aspects will be described in the following sections.

3 Situation-consciousness: the measurement of situation-awareness for Cobot

Since terms around awareness like context-awareness [21], situation-awareness [12, 24, 27], risk-awareness [44] etc. are better studied in the field of automation, the authors start with the awareness. Endsley defines situation-awareness as: “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future” [12]. It has to be noted, that Endsley defined the situation-awareness with the human factors in mind. For this reason, measurement methods as described in [40] do not apply. Nevertheless, this definition itself applies for Cobot. Breaking down this definition, it connects the terms context (environment, time and space, meaning) with the situation and the prediction. According to Dey, the Context C is “any information that can be used to characterize the situation of an entity” [10]. In this case, the entity is the Cobot and the “any information” can be understood as a set of pieces of information. What remains undefined at this point is the term of the situation. The part of “can be used” refers to relevance which is defined by [8]. According to Salfinger, the situation corresponds “to particular state of affairs in the observed environment” [33]. However, instead of speaking about severals situations at the same time, the authors follow [19], who views the situation not only as one state, but rather as a set of states. Moreover, the authors follow [40], where the time and the place are also considered important to characterize a situation. However, [8] point out that the definitions "fall short several steps by failing to provide a clear guidelines to base an implementation upon. They also don't provide an answer to the question of how an agent can achieve Context/Situation Awareness." For this reason, the authors puzzle together the core of the definitions from the literature and try to formalize the definitions in the following way.

Context. The context C depicts a set of objects $O^k = \{O_1, O_2, ..., O_N\}$ around the Cobot and their relations $R^k = \{R^k_{ij}\}$, where $i, j = 1, \dots N$ at the kth discrete point in time: $C^k = \langle O^k, R^k \rangle$. The relation R^k_{ij} describes the relation between the ith and jth objects at the kth point in time. Objects bundle information and are understood in the sense of object oriented paradigm, i.e. they represent not only physical things like obstacles but also immaterial things like geo-fences. As real fences, geo-fences keep mobile robots out. However, they are purely digital. As [41, 42] point out, the context builds on small meta-models to be fast enough for real-time applications. A suggestion of how to detect the objects and its relations using small meta models is described in section 4. The context is connected to the situation via the objects.

Situation. A situation S is the set of states of the objects of the context. In contrast to the context, the situation does not refer to a specific entity. Therefore, the system itself has to be part of the situation. Let x_s be the system's state vector and $X_{O,i}$ the state vector of the i-th object. Then the situation S is the set of the system or object states: $S^k = \{X_s, X_{O,1}, ..., X_{O,N}\}$. Obviously, the system itself is also an object and can be modelled as the 0-th object. In conclusion, the situation can be reformulated as $S^k = \{X_{O,0}, X_{O,1}, ..., X_{O,N}\}$ or simply $S^k = \{X_0, X_1, ..., X_N\}$. As in the case of the context, the situation is related to a point in time k. The relation to the space is relative to the objects in the environment and part of the state vectors. Note that in real robotic systems, there is no ground truth about the context of the same. Rather, the system itself must infer the objects O^k present based on its measured values $M^k = \{M_1, M_2, ..., M_K\}, K \in \mathbb{N}$. A measured value is one output of one sensor at a specific point in time k, e.g. a camera image, a laser scan etc. The ability to derive the context out of the measurements is the context-awareness.

Context-awareness. The context-awareness is the ability to derive the context out of the measurements. Mathematically speaking context-awareness is the mapping $f_{ca} : M^k \rightarrow C^k$.

Situation-awareness. As by the definition of Endsley, the term situation-awareness contains the perception aspect, the comprehension aspect and prediction aspect. The perception aspect creates from a set of measurements a set of Objects $O^k = \{O_1, O_2, \dots, O_N\}$. The comprehension aspect connects the Objects O^k with relations R^k. Together, perception and comprehension form the context C^k. $X^k = \langle O^k, R^k, M^k \rangle$

This is inconsistent with the definition on the left. I am open to include the measurements in the context counting them as part of the definition. If we opt for including the measurements into the context, the formula must be changed: $f_{sa} : \begin{pmatrix} C^k \\ S^k \end{pmatrix} \rightarrow \begin{pmatrix} C^{k+h} \\ S^{k+h} \end{pmatrix}$

The prediction aspect refers to foreseeing the states of the objects in the environment in nearby future. These states of the objects correspond to the definition of the situation S^k. The nearby future is modelled with the prediction horizon h. Putting all the formalisms together, situation-awareness is a function that maps from a set of measurements M^k and the current situation S^k to the context C^k and the future Situation S^{k+h} the prediction horizon $h \in \mathbf{N}_0$.The mapping $f_{sa} : \begin{pmatrix} M^k \\ S^k \end{pmatrix} \rightarrow \begin{pmatrix} C^k \\ S^{k+h} \end{pmatrix}$ therefore describes the situation-awareness. The situational consciousness in the domain of technical system should therefore measure the quality of the function f_{sa}. The problem why the situation-awareness is never perfect in in real-world systems are the uncertainties. The quality of the situation-awareness therefore represents the capability of modelling the system and itself with an acceptable reality-to-simulation gap [26]. If a strong deviation in either C^k or S^{k+h} occurs, this is named a disruptive event.

Disruptive event. A disruptive event is anything that happens, especially something important or unusual that causes the system or environment to deviate strongly from the modelled behavior and is relevant to the system. Consequently, a disruptive event shows off in the system state or the situation.

Loosely speaking, the consciousness is about rarely getting caught surprisingly by disruptive events. Moreover, the system should estimate the size of the reality-to-simulation gap. To this end, it is less important how the individual deviation turns out, but rather to be able to predict in which range the dispersion will lie. The assessment of situation-awareness is divided into consistency quality, context-awareness and model coverage. Together, they form the consciousness. As defined above, the context-awareness denotes the capability of correctly derive the context C^k out of the measurements M^k. In consequence, the estimated context $\hat{C}^k$ should be as close as possible to the actual context C^k. However, due to inaccuracies in the sensory or the models, a gap in the sense of completeness and correctness might occur between estimate and ground truth. Examples for a gap would be misclassification or even total miss of an object. The gap E_C between the estimated contents can be described as

$$E_C = 1 - \frac{\|\hat{C}^k \cap C^k\|_2}{\|\hat{C}^k \cup C^k\|_2}, \tag{1}$$

where $\hat{C}^k \cap C^k$ depicts the subgraphs of the estimated context and the actual context which are identical and $\hat{C}^k \cup C^k$ depicts the joint graphs. As distance metric, the authors propose to adapt the idea of the Levenshtein distance [42] for graphs, counting the required changes to be made in order to change the one graph to the other one. In order to norm the quality to a value between zero and one, the authors introduce the reference value $E_{C,ref}$. This value represents the expected deviations and has to be defined by the user's experience.

Context awareness quality (CAQ) The context quality measures the similarity of the true context with the estimated one and is modelled as:

$$Q_{CAQ} = \begin{cases} 1 - \dfrac{E_C}{E_{C,ref}}, & \text{if } E_C \leq E_{C,ref} \\ 0, & \text{otherwhise} \end{cases} \tag{2}$$

The second quality metric is the consistency. Consistency quality denotes the degree of freedom from contradiction. Contradictions may occur if different sensors or models conclude non-identical states of the situation. A classic example would be redundant sensory deviating in their results. Inconsistencies may also occur, if predictions are inaccurate. The quantitative use of reasoning techniques that incorporate context uncertainty such as Bayesian networks [10] and fuzzy logic [7]. [20] For example, in quantizing environment sound intensity, the quantization divides the processed feature into three quantities—Silent, Moderate, and Loud—corresponding to the three membership functions The degree of consistency is measured by the weighted deviation of the individual sources of information with the same measurand from the estimated true value. Since the importance for the different states differ, sources must be weighted according to their significance. For example, an estimate should be rated less significant than a measurement. Following the maximum likelihood approach, the following state estimate evolves:

State Estimate. Let $K_{i,j}$ be the vector, which summarizes all redundant measured or estimated values of the j-th coordinate of the state vector $X_i \in \hat{S}_n$. Let further $\hat{S}_n$ be the estimated situation corresponding to the estimated context $\hat{C}_n$. Now, the state estimate $\hat{k}_{i,j}$ is the scalar product of a weighting vector and the measurements: $\hat{k}_{i,j} = \gamma \cdot K_{i,j}$. Consequently, the estimated state vector $\hat{X}_i = (\hat{k}_{i,1}, \hat{k}_{i,2}, ..., \hat{k}_{i,N})$.

Following the quality measurment scheme, the error vector of the system state $E_{Con,i}$ is $E_{Con,i} = \|\hat{X} - X\|$. Again, the consistency quality is normed to a reference error vector $E_{Con,ref}$, which predicts the maximum deviation of the sources and negatively correlates with the consistency errors. This value has to be set out of the experience. The definition of the consistency quality is given below:

Consistency Gap Awareness Quality (CGAQ) The Consistency Quality measures the similarity of all different information sources representing the same quantity of the situation's state vectors. Let $E_{Con} = (E_{Con,1}, E_{Con,2}, ..., E_{Con,N})$ be the vector that summarizes all i discrepancies in the state vectors X_i. Then the consistency quality is modelled as:

$$Q_{CGAQ} = \begin{cases} 1 - \dfrac{E_{Con}}{E_{Con,ref}}, & \text{if } E_{Con} \leq E_{Con,ref} \\ 0, & \text{otherwhise} \end{cases} \tag{3}$$

Finally, the degree of coverage (i.e. coverage quality) of the models is to be defined mathematically. Loosely speaking, the coverage quality represents the certainty of not getting caught by surprise, where surprise is as defined in [8]. More formally, the degree of coverage describes the ability of the system to correctly model possible scenarios s_i. A scenario is a sequence of events. It can be described by the probability that the system correctly assesses the situation and its own state. For this purpose, the measurement of the degree of coverage builds on the previously defined quality metric of consistency:

Model Coverage Quality (MCQ) The model coverage quality measures the probability that the currently active set of models is capable of modelling the system behavior accurately. Let Q_C be the context-modelling quality as defined in (1), Q_{Con} be the consistency quality as defined in (2). Let further s_i be a randomly selected, possible scenario. Then the MCQ is:

$$Q_{MCQ} = P(Q_C > 0 \cup Q_{Con} > 0 \mid s_i) \tag{4}$$

The suggested approach to determine Q_{MCQ} follows the frequentist approach to count the number of different scenarios between two violations of the criterion $Q_{CAQ} > 0 \vee Q_{CGAQ} > 0$ respectively. To this end, the consciousness of a Cobot is defined as follows: Situation-Consciousness. The Situation-Consciousness ζ describes the level of situation-awareness. Let Q_{CAQ} be the Context Quality as defined in (1), Q_{CGAQ} be the Consistency Quality as defined in (2) and Q_{MCQ} be the Coverage Quality as defined in (3). Then, the Situation-Consciousness is the tuple $\zeta = \langle Q_{CAQ}, Q_{CGAQ}, Q_{MCQ} \rangle$

4 The process of improving situation-awareness

Having formally defined the consciousness, in this section a systematic method to improving this consciousness is presented. As initially discussed, consciousness is related to awareness. According to [12], the awareness of automated systems follows a three-step process: Perception, Comprehension, and Projection. However, this process is focused on the human operator. Table 1 maps this situation-awareness process to situation-awareness of Cobot.

This adapted framework manifests in the structure as visualized in Fig. 1. check it - perception, comprehension and projection? - Tamas The first step in this process is the measurement of the consistency quality, which happens in the Perception step. In this step, the intelligent Digital Twin joins the data from the real world (asset) and predictions or estimates from the cyber world and compares them. As a result, the intelligent Digital Twin estimates the true state, the error and thus the CGAQ Q_{CGAQ} to the Comprehension step. The Comprehension step joins context estimation from the virtual world and context mining on real-world data to provide the further quality estimates, namely the context quality and the coverage quality. From this comprehension, the intelligent Digital Twin draws conclusions in the Projection step. In this step, a reinforcement learning model generates a correction model. This correction model is later on tested against collected real-world data in order to validate generalization to previously observed situations. In the virtual world, the intelligent Digital Twin predicts the situation S^{k+h}, which serves as witness to validate the quality of the updated model. Change management holds the previous model as fallback solution. To avoid misunderstanding, the

Table 1 Adapted situation-awareness for mobile robots

Steps	Interpretation for Cobot
Perception	Perceive deviations from forecast. Perceive deviations between models. Perceive disruptive events.
Comprehension	Anomaly detection. Retrieve the context around the system. Characterize disruptive events.
Projection	Generation of context model. Generate context model. Synchronize model and asset. Predict future situation.

Digital Twin communicates the changes to the human workers.

The consciousness building process exploits the intelligent Digital Twin's knowledge. This knowledge consists of different models like the physics models, the context models, statistical models and quality models. In the execute step, exactly these models are updated. In this way, the knowledge grows with the experience the intelligent Digital Twin makes during operation, adapting the Digital Twin to the environment it is deployed in. The following subsections describe this situation-awareness process in detail.

4.1 Perception

The intelligent Digital Twin uses the perception step to perceive itself interacting within the environment (Fig. 2). Key to this step is to build an expectation of the situation $\hat{S}$, i.e. the state vectors $\hat{X}_i$ and compare them to the available information. However, as [25] shows, synthetic data from simulators differs significantly from real-world process data. In general, models simplify the reality and therefore by design need to be made comparable first. On the other hand, real-world data requires to be cleaned up first, in order to reduce the complexity to the relevant aspects. To this end, the intelligent Digital Twin executes the stages: data acquisition, pre-processing and transfer. It differentiates both domains: cyber and physical world.

In the cyber domain, the simulation environment produces synthetic data. Normally, this data represent a subset of the total space of possibilities the system acts in. It is very specific to the simulated case. In order to make the data more general, the noise and dirt effects might be added. Moreover, to prepare the system for real-world data, the intelligent Digital Twin extends the covered exploiting Domain Randomization. Concrete approaches of how this works are proposed in [37]. The result of this Domain Randomization are synthetic features, which have to be unified in order to match the process features. In this context, it has to be noted, that the algorithms in the simulation domain might differ from the algorithms in the physical space. The Simulation-to-Reality Wrapper takes care on this task. It puts the detection layer on a higher level and therefore eases the comparison. One example is the domain of object detection. In this area, not only the identified label but also the confusion matrix to other labels should be considered. However, reducing this matrix to the 5-10 most relevant misclassifications and comparing this between cyber world and reality is better comparable than comparing the features, which the object detectors use. In the physical world, the sensory acquires the process data of the asset. Since the issues of real-world data are opposite to synthetic data, the Digital Twin aims to purify the data. For this purpose, the Digital Twin exploits Sensor fusion and noise reduction techniques to pre-process the data. As an example, the multiple measurements of a LiDAR sensor suggest different positions in the room. Using the Kalman filter-based simultaneous localization and mapping, the Digital Twin merges these values to provide one feature: the most likely position in the map. Based on the process features, the Reality-to-Simulation Wrapper further abstracts from the channel-specific aspects. Taking up the example of the LiDAR, the position information is provided relatively to the robot position. If now the prediction of where to find a moving object in the map shall be compared, the Reality-to-Simulation Wrapper has to transform the detected objects to the map in order to compare the simulated position of the object with the actual one. Running these three steps, the comparison of estimation of the actual value with the value available in the model or sensor can be applied to models in general, as long as a set of comparable features can be extracted. In the case of physical models, physical state variables such as position, velocity, and orientation can be compared. In the case of context models, e.g. the degrees of membership can be used. On top of that, the perception can also be extended by external feedback, e.g. by a worker. This corresponds to an extension of the vector K_j or $S_{r,j}$. As the monitoring step makes the different models comparable in the state vectors K_j and $S^k_{r,j}$, the Digital Twin calculates the Consistency Quality Q_{CGAQ}. Having perceived the environment, the next step is to make sense of these perceptions. This step is described in the following subsection.

4.2 Comprehension

The Comprehension step analyzes the statistical properties of the perceptions, classifies the context

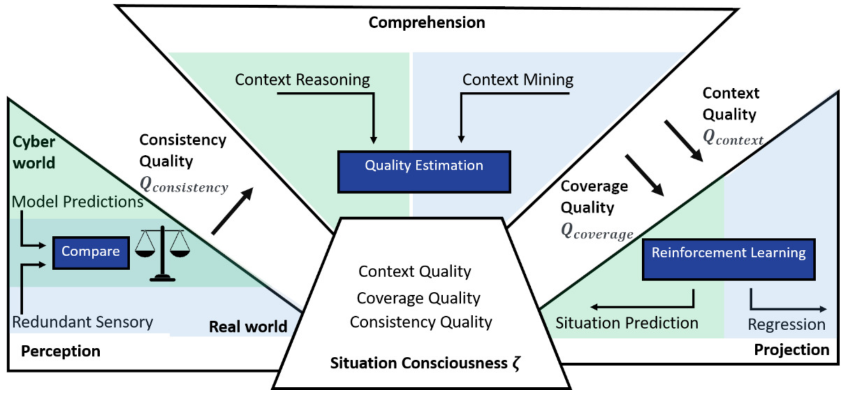

Fig. 1 Situation-awareness scheme building consciousness

and analyzes the coverage quality of the intelligent Digital Twin. Fig. 4 visualizes this step. The process starts to distinguish the normal and the abnormal data using anomaly detection. In this paper, the anomaly detection is limited to Consistency Quality for the next time step. As the $Q_{CGAQ} = 0$ already defines that the models are not adequate to describe the respective scenario, this quantity is a natural measure for anomalies. For an exhaustive view on this topic, Lindeman et al. [22] provide a comprehensive survey. In a way, the sophisticated methods allow for comparing different time steps in parallel to identify more types of anomalies. Having analyzed the data for anomalies, the context comes into the focus. Depending on whether an anomaly is detected or not, the intelligent Digital Twin relies on either the virtual or the physical world. As an anomaly indicates that the models (i.e. the virtual world) are not sufficiently accurate, the intelligent Digital Twin relies on the real-world data to perform context mining. Fig. 3 visualizes the process of context recognition. The context recognition bases on a set of small meta-models as proposed by [41, 42]. From the meta model, the Relation Mapping gets the information of what to search for in the sensor data. In this way, the Relation Mapping determines relations between the recognized objects. The subsequent Model Matching takes the relations and search patterns from meta models to check which meta-model to instantiate to create a set of models. The meta model imprivement cycle is excluded from the scope of this work and left for future work. - MM.

Examples for contextual information are links between obstacles as table feet linked to their tabletop. The first task is to identify similar situations using clustering algorithms. For this purpose, one distance criterion certainly exists, the consistency error E_{Con}. If the consistency errors have a common root, a similarly high error is expected. However, since this first stage is very rough, a detailed look into the elements E_{r,S_i}.and

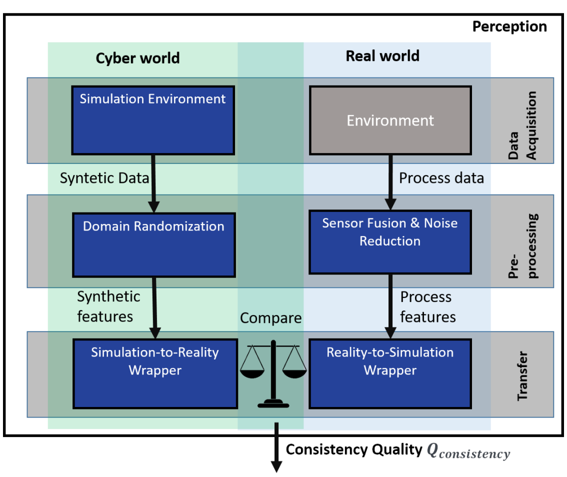

Fig. 2 The perception step

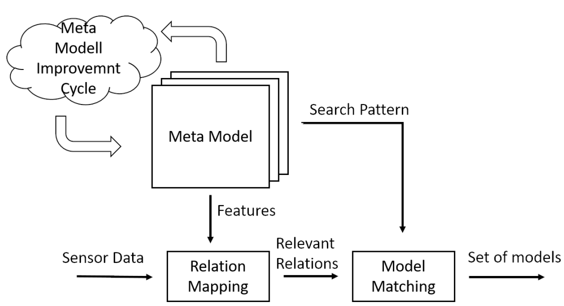

Fig. 3 Context Recognition

E_{r,K_j} bring better insights. If a certain object is changed or missing in a situation and a significant change in a signal occurs (e.g. transition from normal to abnormal), the object and the signal are linked. Furthermore, if a set of objects always occurs ensemble, they are also linked together. The detailed similarity metric is a design decision. In the case of mobile robots, for example, trajectories or the error in their measurement or prediction could serve this purpose. To this end, comparing the data of the current perception with the previous one, similarities point to characteristic features of the disruptive event and allow for reasoning about which objects are linked. Having a set of features characterizing a certain scenario and observing it for several times, the reality-to-simulation gap can be modeled better and better. In this way, the intelligent Digital Twin estimates the impact of the disruptive events. Putting the clustering and the impact analysis together, a situation is put in their context and disturbing events are characterized. However, this method can only reveal correlations, not causality. To cover causality, the observation must be validated by another instance. In case of normal data, the available models prove usable. As the predictions fit, the estimated context comes close to the estimated one. The intelligent Digital Twin analyzes the frequently occurring patterns connected to a specific context. Exemplarily, the intelligent Digital Twin estimates probability of certain objects or conditions (represented in the situation S) occur in a given context. In this way, the estimate of the ground truth situation S is supplemented by elements that with very high probability are also present in the current situation. Similarly, discarded objects close to the detection threshold may be considered in S. Moreover, engineering knowledge flows into both, the estimated situation and the assumed ground truth. For example, the tabletop is hard to detect for 2d laser scanner. However, form the table's legs, if they stand in a certain distance, you can conclude that this should be a table. From these data, the current context reveals that a further object exists, namely the tabletop, which is invisible for the sensory. Having analyzed the context in this way, the system has both variables available and therefore calculates the Context Quality.

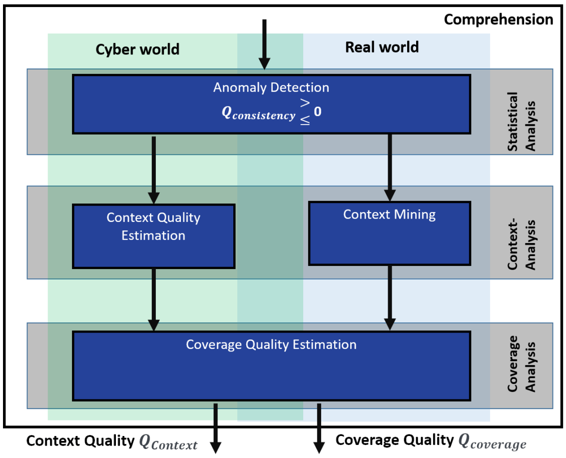

Fig. 4 The comprehension step

In the subsequent coverage analysis, the system checks whether a similar case has occurred already. Only if current situation is new to the system, the coverage quality estimate changes. In case of abnormal data, the system obviously was unable to measure or predict the environment properly which yields the coverage quality estimate to drop. In the case of normal data, the coverage quality rises respectively.

As a result, the comprehension step provides the context quality and the coverage quality. Based on these analyses, the intelligent Digital Twin projects the future development of the situation. This step is described in the following section.

4.3 Projection

The final step of the situation-awareness scheme is the projection. In this step (see on Fig. 5), the future situation S^{k+h} is predicted based on an updated version of the models. In order to update the model, the intelligent Digital Twin creates a data-driven correction model, which depends on the context. For this purpose, the Data Selector chooses the samples from the real-world data based on the similarity to the current context. Based on these training data, a machine learning algorithms creates a policy that takes the output of the original model and modifies it such that it gets closer to the actual value. The authors suggest using offline reinforcement learning where the consistency quality serves as reward. Disruptive event limit the area, where the correction model is valid. Andaluceia et al call this scenario space

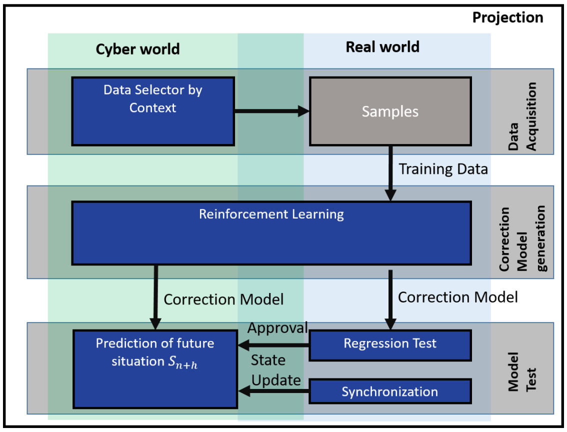

Fig. 5 The projection step

a dependability cage [1]. However, with growing sample size, the agents learn from the event features and the error between predicted and actual states how to compensate them. A new correction model for the new context arises. Once the model converges, the additional samples for the same context extend the dependability cages. The intelligent Digital Twin gains confidence in which context the respective updated models are appropriate. Generally, the updated models first run in parallel with the existing models in a test phase. In this test phase, regression tests are performed. Once confidence in the model's quality, the intelligent Digital Twin approves the sandboxed models and turns them to productive mode. For the case of unintended behavior, the model contains a link to the old model, which serves as a fallback plan. Having updated and approved the models, the prediction of the future situation takes place. For this purpose, the intelligent Digital Twin first synchronizes the models with the asset. During the synchronization, all the system states and the situation states in the models are set to their most likely values $\hat{X}_{r,j}$ and $\hat{S}_{r,l}$. These updated states are feed to the prediction module. Based on the updated states and models, the prediction module predicts the future Situation S^{k+h}.

extend it - Tamas Finally, the intelligent Digital Twin communicates the situation-consciousness of the system to the user. This step is described in the following section.

4.4 Communication of the consciousness using intelligent Digital Twin

The communication of the situation-consciousness contains on the one hand the visualization of the models. The intelligent Digital Twin shows the ongoing processes in simulations based on the real-time data exchange. For example, the map and the simulated movement of the Cobot together with incoming camera frames are shown in real-time. Tablets might server as a frontend to display the visualization. In this way, the worker can inspect and analyze the consciousness of the Cobot. If less details are required, a management board shows the former introduced metrics, namely the coverage quality, the consistency quality, and allow for checking out specific consistency errors.

5 Experiments and Results

To study the situation-consciousness, a cyber-physical model factory with mobile robot platform of type Robotino 3 Premium by Festo, an automated storage and 4 workstations are considered. The Robotino serves as a collaborative robot and is focused in this work. The mobile robot uses a laser scanner for Simultaneous Localization and Mapping (SLAM). A monocular camera assists the object detection and visualizes the environment. For communication interface, a Robot Operating System (ROS) node runs on the robot, providing a service-oriented interface. A PC running Lubuntu 20.04 controls the Robotino wirelessly through this ROS node. It mimics a cloud server and is equipped with an i9 processor and NVIDIA P620 graphics card. The simulation environment builds on Gazebo. Grid maps generated by the laser scanner and reinforcement learning models complement it. The framework RviZ serves for visualization.

For this system, an intelligent Digital Twin is set up. Fig. 6 illustrates Robtino within the cyber-physical factory and its intelligent Digital Twin. The robot's intelligent Digital Twin manages safe navigation in the factory, but also in a bureau environment. The robot works closely together with human workers, providing tools, workpieces etc. When working closely with robots, it is critical that the worker understands the robot's situation-consciousness. To this end, the authors take the continuous example of correct movement and positioning of the robot in simulation and reality. This example is deliberately chosen simple, to outline the idea. More complex examples complement the continuous example covering various aspects of the robot and its Digital Twin. For the positioning, the laser scanner data is processed to extract the position using SLAM. On its journey, the robot perceives objects like the workstations, but also elements of the bureau environment like tables. The aim of this scenario is to display the development of the robot's consciousness. To evaluate the process of developing consciousness and its communication to humans, the experiments follow the previous section structure.

One major task of the intelligent Digital Twin is to communicate the insights that the mobile robot has about its environment. Specifically, the human workers need a clue, where the system perceives the environment differently than the worker would expect. In this context, it is crucial to visualize the intelligent Digital Twin. Fig. 6 (left-bottom) illustrates the perception of the intelligent Digital Twin. The laser scanner detects I-shaped tables. Through pattern recognition, the robot maps it to a table, which the intelligent Digital Twin represents as the white bounding boxes, where the robot must not enter. The perception of the robot is structured in several views, which the worker selects in the tool bar on the left hand side. The map in shows the current laser scanner measurement (cyan), the direction of movement (red arrow), and the assigned grid maps that mark the forbidden regions. The terminal on the bottom right gives feedback about the running scripts.

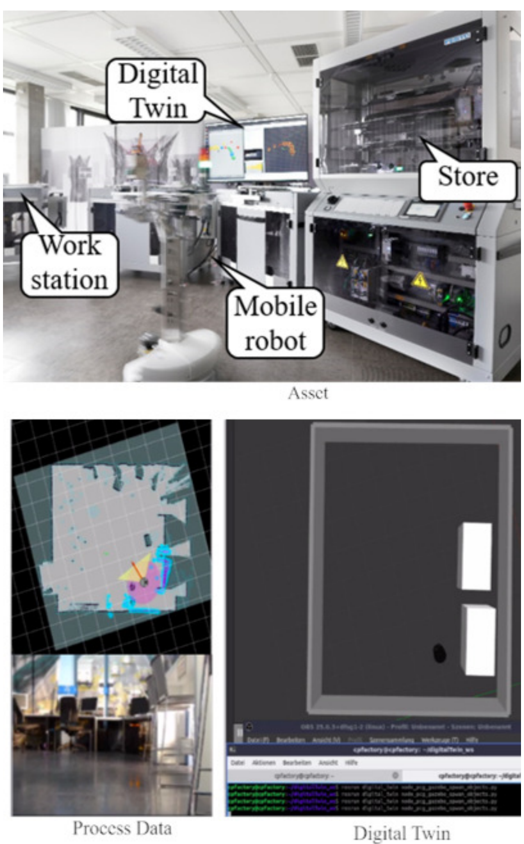

Fig. 6 Visualization of the Cobot and its intelligent Digital Twin

The experiment results are discussed in this section through the previously detailed process steps. The calculation of the consistency quality for positioning is described in Section 5.1 and the comprehension step for anomaly detection in Section 5.2. Finally, the results of the projection step are detailed in Section 5.3.

5.1 Perception

The perception step shows the calculation of the Consistency Quality for the positioning. Moreover, the position of the obstacles in the map are evaluated. To keep it simple, the experiment is limited to these two aspects. Having in mind tight collaboration with human workers, the reference error $E_{Con,ref}$ is set to a maximum simulation-to-reality gap of $2\,cm$. In the simulation, the position calculation uses a simple physics model, assuming the speed controller always swung in and therefore $s(t) = s_0 + v(t) \cdot t$ applies. However, in the drive of the autonomous mobile robot, two nonlinearities exist, which the models do not take into account. This yields to poor model quality, which is detected and quantified in this step. As reference, the laser scanner evaluates the position from several data points referenced to known objects. Transforming the slam position into the simulation coordinates the simulated positions and the measured ones get comparable. Fig. 7 shows the results without compensation. In average, every third position value exceeds the reference error $E_{Con,ref}$ (marked red). Whenever, this happens, the system resets the simulated position to the measured value resulting in frequent synchronizations. Although the synchronizations were this

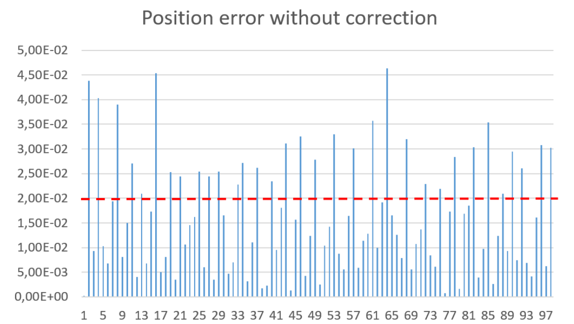

Fig. 7 Deviation of the position before compensation and error reference

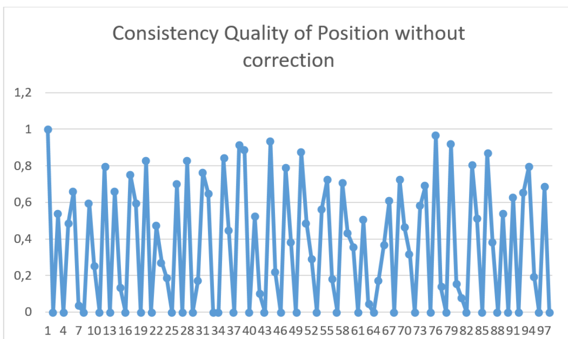

Fig. 8 Consistency Quality before the compensation. $Mean = 35.5\%$

frequent, still deviations above $2 \cdot E_{Con,ref}$ occur. This makes the autonomous mobile robot "jump" in the simulation environment. As expected, the initial model quality is therefore rather poor. Fig. 8 shows the calculated consistency quality Q_{CGAQ}.

5.2 Comprehension

The comprehension step starts with anomaly detection. An anomaly is detected whenever the consistency quality $Q_{CGAQ} = 0$. As visualized in Fig. 8, this happens 34 times in the uncompensated data record.

For this reason, the authors extend the example with the object detection and context mining thereof. Consider the maps in Fig. 9 and the mapping table in Fig. 9 (left) shows the grid map as the laser scanner records it. In Fig. 9 (right) the object detection identifies additional closed areas based on the mapping table in Fig. 10. This mapping table uses the context of the detected objects to each other for the object identification and the respective representation in the grid map.

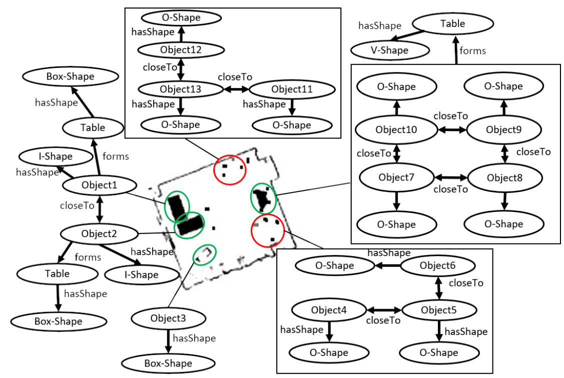

Fig. 9 Object detection based on context models

As Fig. 10 shows, the laser scanner perceives the table feet as single object in a certain distance (relation). In this way, the detection is invariant against rotations. Moreover, this representation allows for the calculation of the Context Quality. Things are easy as long as all the feet are detected properly. However, if only three of the four feet are detected, the table will not make it into the estimated context $\hat{C}^k$, but in the reference context C^k. In the red marked circle, the algorithm estimates no table, but with considerable probability, it could also be a table. Only three of four feet are detected properly. In fact, they are tables, but melt with the background. In conclusion, the object detection properly detects four out of six objects (marked green). For the two tables, a table food is missing each. In consequence, using the Levenshtein distance, 2 close To-relations and 1 O-Shape object needs to be added. On top of this, the detector misses that the objects form a table of shape V-Shape. In total, for each missed table 2 objects and 4 relations are missing. In total, there are 19 objects and 36 relations, where 16 objects and 28 relations are detected properly and do not require any change. For simplicity, each operation (i.e. add relation or add object) count equally. The context error is therefore calculated according to (1): $E_{Con} = 1 - \frac{(16+28)}{(19+36)} = 0.20$. The reference is $E_{Con,ref} = 1$, which leads to a context quality $Q_{CGAQ} = 1 - 0.20 = 80.0\%$.

In the case, where the data is classified abnormal, data mining is executed on the real-world data. Taking for example the camera as an additional information source, the former wrongly classified tables (marked red) become observable. With this information, the algorithm learns that several tables in a row and tables too close to

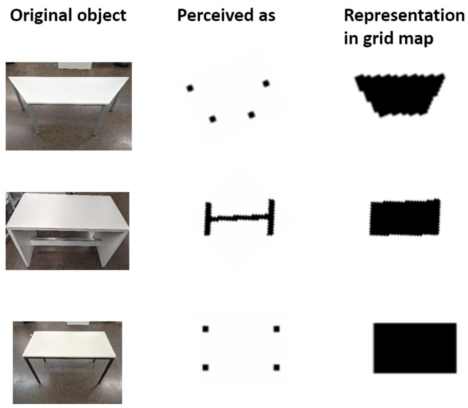

Fig. 10 Object detection rule table

the wall characterize the false classifications. This reveals limitations in the laser scanner based object detection. In this research area, [32] propose more sophisticated methods to extract context features. The next step is calculating the coverage quality. As a naïve approach, every scenario is classified new, which leads to a coverage quality as plotted in Fig. 11. The estimated coverage quality is simply calculated as ratio of the covered cases to the whole amount of cases. The coverage estimate converges towards $Q_{MCQ} = 66\%$.

5.3 Projection

The projection step starts with the collection of samples associated with the respective context. With these training data, a reinforcement learning agent is trained. The parameters of this reinforcement learning algorithm are given in Table 2.

The reinforcement learning algorithm compares the model's position value before and after

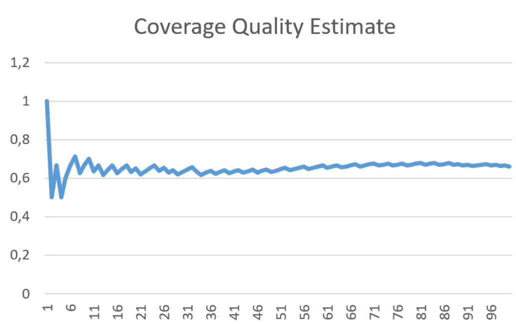

Fig. 11 Estimated Coverage Quality over samples without adaption. Mean = 66%.

Table 2 Reinforcement Learning Algrithm Portrait

Parameter	Value
Algorithm class	State-Action-Reward-State-Action
Available input	Continuous value, Delayed reward, Multi-action
Assumptions	Only longitudinal control
Action space	$0 \ldots 20cms^{-1}$, quantization $1cms^{-1}$
Reward	$R(x) = \begin{cases} +1 & \text{if } x < 1cm \\ -5, & \text{otherwhise} \end{cases}.$
End of an episode	$x > 2cm$ or rotational deviation $> 0.01rad$.

applying synchronization. The improved model is not applied directly but runs in parallel to the original model until it is considered stable and executed (see next section). The analysis step, specifically the context analysis and the anomaly detection supply the reinforcement learning agent with samples. The synchronization process takes the measurements from the laser scanner and processes it to position information using SLAM algorithm. This position measurement is validated through reference measurement. The synchronization module now compares this position to the simulated position. In consequence, the reinforcement learning algorithm comes up with a mapping table that maps the original speed ("old action") to the better fitting velocity ("new action"). The mapping from old action to new action is visualized in Fig. 12.

This experiment shows that the resulting model is too simple. Up to the velocity of $6\frac{cm}{s}$ a start-up inhibition can be observed. Obviously, the controller is not able to adjust motions below this level. In addition, the graph shows velocity saturation at $16cm^{-1}$. The physical controller seems to have a limit at this value, rather than at the assumed $20cm^{-1}$. Reasons for this behaviour could be friction, etc., using up the control reserves. Both nonlinearities are plausible and were validated at the physical asset. Of course, such deficiencies can be corrected manually. However, the amazing thing about this approach is that the system automatically detected the problem in the model (i.e., found the limits of the model) and improved it to compensate for the deficiencies. This increases the Consistency Quality and the Coverage Quality as shown in the following section. The model also provides the ability to specify context features more precisely. Thus, 3 domains emerge: The start-up range up to $6\frac{cm}{s}$, the linear range $[6 \ldots 16]$ and the saturation range $> 16\frac{cm}{s}$.

Applying this compensation shows a significant improvement of the model as visualized in Fig. 13. The new model applies the improvement using reinforcement learning. The results are visualized in Fig. 14. As can be seen, not only the number of deviations was reduced from 33 to 10, approximately a third compared to the old model, the magnitude of the deviation was also reduced. In other words, the model got three times closer to the actual position, an improvement by 300%.

As a consequence, the Coverage Quality in the updated scenario reaches $Q_{coverage} = 91.3\%$. Comparing the quality metrics before and after the situation-awareness process, a

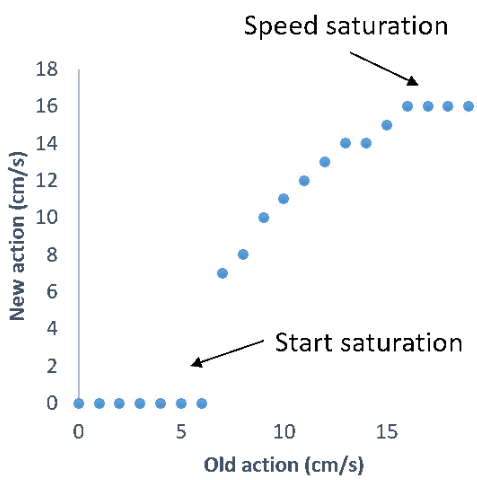

Fig. 12 Position Error after Adaption background should be transparent

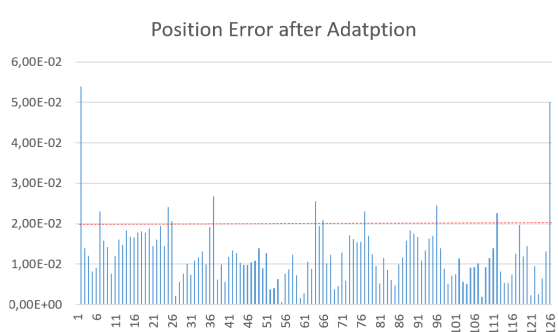

Fig. 13 Position Error after Adaption

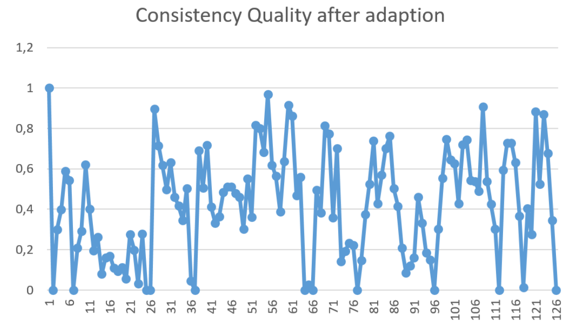

Fig. 14 Consistency quality after Adaption ($Mean$ = 42.3%)

clear improvement is notable. Having measured an initial situation-consciousness $\zeta_{unadapted} = \langle Q_{CAQ}, Q_{CGAQ}, Q_{MCQ} \rangle = \langle 80.0\%, 35.5\%, 66.0\% \rangle$, during the situation-awareness process, the situation-consciousness increased to $\zeta_{adapted} = \langle 80.0\%, 42.3\%, 91.3\% \rangle$. At this point, no change in the Context Quality happens since the reference value for the context detection does not trigger an adaption process. The authors leaf the improvement for the context quality for future work.

6 Conclusion

Digital Twin is missing

The degree of situation-awareness is crucial for smooth cooperation between humans and machines. Only if the human understands how well the robot is aware of its environment can the human worker adapt her behavior appropriately, like moving in the other direction, preparing for the approaching, or moving farther from the robot. In this paper, the measurement of the situation-awareness, the situation-consciousness was introduced for the domain of collaborative robots based on the intelligent Digital Twin. The situation-consciousness is a quality metric containing three components: the Context Quality, the Consistency Quality, and the Coverage Quality. Together, the tuple describes the state of situation-awareness. Following the three-step process of situation-awareness, a scheme for improving the situation-consciousness was proposed and evaluated on the example of the positioning of the mobile robot platform Robotino. The intelligent Digital Twin handles the simulations and the real-time communications through the sensors and visualization equipment.

The experiment shows that the quality metric is applicable to the robot system and qualitatively represents the state of situation-awareness. Moreover, the improvement process for the situation-awareness increased the Consistency Quality from 35.5% to 42.3%, and the Coverage Quality from 66.0% to 91.3%. In conclusion, the system covered 25% more cases than before where at the same time reducing the reality-to-simulation gap by 10%. The improvement process for the context quality is left for future work.

Acknowledgment

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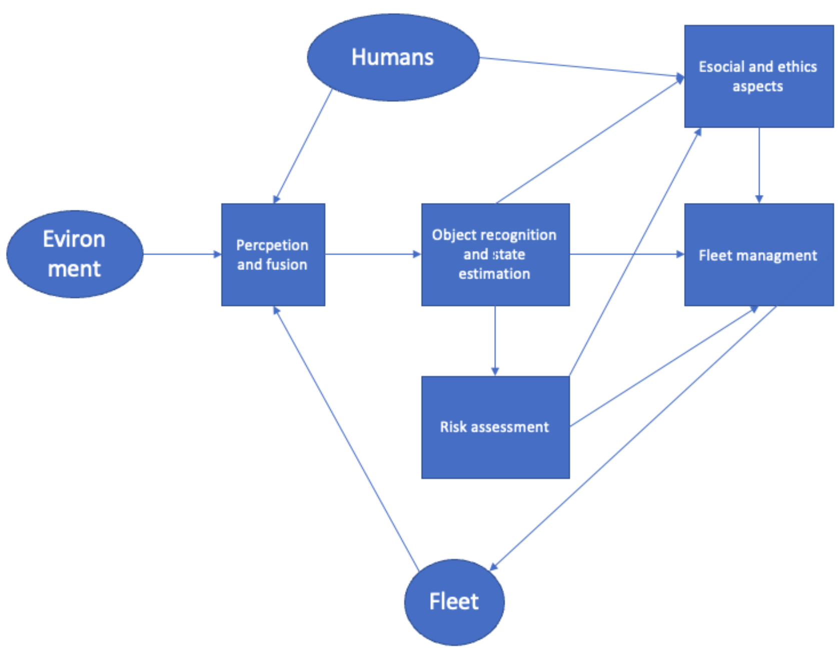
Call name: AI for human empowerment (AI, Data and Robotics Partnership) (RIA)
Topic ID: HORIZON-CL4-2022-HUMAN-02-01
Link: https://bit.ly/3o8gcRB
WPs: Horizon-CertainShopfloor-WorkPlan

Manufacturing shop floors and warehouses have Automated Guided Vehicles (AGVs), manually driven vehicles, e.g., forklifts, and human operators in shared areas. Nowadays, AGVs tend to be controlled by complex software with AI. This software has to find optimal and safe routes that will be commanded for AGVs and recommended to human drivers. However, performance-optimal solutions are not always the best ones. The following scenario could happen: the AI assigns more trips to forklift driver A than to his colleague driver B because driver A is normally faster than B. This inequality increases with time. Driver A completes his assignments ever faster because otherwise, he would be unable to keep up. Driver A becomes inattentive at some point and is increasingly exhausted. This situation results not only in physical and environmental risk but also poses psychological hazards to both drivers. Driver A might burn out, and drive B will be highly demotivated. The situation is also questionable from an ethical perspective.

Usually, in complex human-machine systems, psychological concerns are only investigated before or during system deployment. Ethical concerns are not systematically covered by occupational health and safety measures at all. Early identification of possible software tendencies to contribute to the development of moral values and norms and adapt ethical criteria to the specific deployment contexts, tasks, and users are essential for the transition to the human-centric Industry 5.0.

Considering these aspects, we aim to define the psychological and ethical criteria for manufacturing shop floors and warehouses and demonstrate how AI algorithms will fulfill this standard. We plan to achieve this goal via interdisciplinary work on the following topics:

1. Social and ethical aspect (Larissa, please improve)
    a. Define the physiological requirements for the human-centric solutions
    b. Human-Machine Interface definitions
    c. Ethical standards development for the AI-driven solutions
2. Reliable indoor tracking
    a. Tracking of the human, and the manual and automated vehicles
    b. Utilize LiDAR, Indoor Positioning Systems, UWB, and the additional sensors
    c. Object detection and recognition
3. Navigation for humans and automated assets
    a. Human-centered workload optimization based on the developed ethical standard
    b. Efficient real-time navigation
4. AI-based state estimation and risks assessments
    a. Integrated state estimation (layout, vehicles, process)
    b. AI-based prediction of future vehicle states and uncertainties
    c. Risk estimation algorithm (near miss accident recognition)
    d. Reaction of human on potential safety measures
5. …



Universität Stuttgart
Institut für Automatisierungstechnik und Softwaresysteme

27th IEEE International Conference on
Emerging Technologies and Factory Automation

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Human-centered knowledge graph-based design concept for collaborative manufacturing

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***Abstract*—With the increasing importance of highly connected and monitored processes supported by industrial information systems, such as knowledge graphs, the integration of the operator has become urgent due to its high cost and is also to be appreciated from a social point of view. The facilitation of collaboration between humans and machines is a fundamental target for Industrial Cyber-Physical Systems, as the workforce is the most agile and flexible manufacturing resource. Furthermore, the design of such a framework requires effective systems to utilise resources and information. This paper aims to provide recommendations of ontologies and standards that can support monitoring work conditions, scheduling, planning and supporting the operator and the possibilities to formalise the classic work instructions to analyse the unique activities. The main contributions of the work are that it proposes a design work-frame of a knowledge graph where the work performed by the operator is in the scope, including the evaluation of movements, collaboration with machines, work steps, ergonomics and other conditions. The paper highlights that activity recognition technologies can enhance the utilisable data in a knowledge graph for a smart factory. With this approach, the future goal may be to automate the entire data collection and knowledge exploration processes, which can facilitate the support of the human-digital twin and the implementation of augmented reality technologies in the Industry 5.0 concept.**

***Index Terms*—Ontology, Knowledge Graph, Human-centered, Manufacturing, Industry 5.0**

I. Introduction

A strong necessity to increase productivity while not removing human workers from the manufacturing industry creates challenges for the global economy and developers of MES (Manufacturing Execution System) or ERP (Enterprise Resource Planning) systems, where the operator is still not sufficiently integrated. The related industry standards, semantic models, and supporting solutions to this problem are reviewed, starting with the ISA-95 standard. Moreover, the main goal is to propose a knowledge-graph framework for the modeling, supporting, and scheduling of the operator, where in addition to efficient data collection, the work of the operator can be facilitated by the use of a knowledge graph (KG) and the implementation of Industry 5.0 technologies becomes possible.

The main aspects of Industry 4.0 aim the extensive digitalisation, while in an Industry 5.0 environment, the goal is to integrate innovative technologies with human actors, which can be stated as a more value-driven than technology-driven approach [1]. Industry 4.0 focuses less on the original principles of social fairness and sustainability and more on digitalisation and artificial intelligence-driven technologies to increase flexibility and efficiency [2]. Industry 5.0 complements and extends the main features of Industry 4.0. At the same time, it provides a different focus and highlights the importance of research and innovation to support industry in its long-term service to humanity [2]. Additionally the research interest is emerging in aspects of industrial humanization [3], sustainability and resilience [4].

From this motivation, the concept of Industry 5.0 [5] is considered, where robots are intertwined with the human brain and work as a collaborator instead of a competitor. Integrating all parts of production, business processes, and Information and Communications Technologies makes it possible to form a complete digital copy of production as a digital twin. Therefore, a reflection of all fundamental physical processes in a virtual production model is achieved, but the results of digital modeling can provide feedback and create a control effect on real production processes, which is an integral part of the concept of Industry 5.0 [6]. It is considered that the human influence on the Cyber-physical system (CPS) has always been present and has always played a dominant role in the formation and development of the CPS. Therefore, human intelligence is a dominant and decisive factor in intelligent manufacturing, which view is consistent with the Human- Cyber-Physical Systems (H-CPS) concept [7].

For adequate human-machine integration, the *Operator 4.0* concept [8] needs to be assessed, which aims the adaptive automation toward human-automation symbiosis work systems for a socially sustainable manufacturing workforce. The purpose of these researches is to develop automation-aided systems, which provide a sustainable relief of physical or mental stress and support the development of workforce creativity, innovation, and improvisational skills, without compromising production objectives [8]. A more recent study proposes the *Resilient Operator 5.0* concept [9] about how to make human operators more resilient against the factors affecting their work and workplaces, which supports the achievement of an appropriate smart manufacturing system.

The ontologies and industrial standards reviewed and suggested in this article help design systems that allow operators to become more resilient, have less dependency, more flexibility, or have a better-designed work order. In the near future, by evolving virtual and augmented reality (AR) tools, the ability to have a hardware and software interface will become more and more demanded. For example, gesture-based interfaces, tangible interfaces, wearable electronics, and sensor network-based interfaces are indicated as today's rising trends [10].

Information management of these emerging development trends requires an effective solution as knowledge graphs, which use a graph-based data model to capture knowledge in application scenarios that involve integrating, managing and extracting value from diverse data sources, even at a large scale [11]. Knowledge graph methods can mine information from structured, semi-structured or even unstructured data sources, and finally integrate the information into knowledge, represented in a graph [12].

The main contribution of the paper is proposed in Section II, where the building elements of the Human-centered knowledge graph-based design concept are defined. Section III introduces the industry standard-based modeling of the operator. In Section IV the knowledge graph-based support of the operator in human activity recognition (subsection IV-A) and collaboration aspects (subsection IV-B) are discussed further.

II. Human-centered ontology towards smart collaboration in manufacturing

In this section, the main contribution of this paper, the Human-centered knowledge graph-based design concept, is introduced, then the operator modeling and supporting approach are discussed in more detail. In Figure 1 the main building blocks of the operator-centric concept are visualised, where the synergy of the three elements creates the *Human-centered knowledge graph* in the middle.

The *Industrial standards* are the first elements, such as the ISA-95, B2MML (Business To Manufacturing Markup Language), or AutomationML. The extension of the already existing standards is recommended, such as the ISA-95, to support the work of operators. An essential aspect of industrial

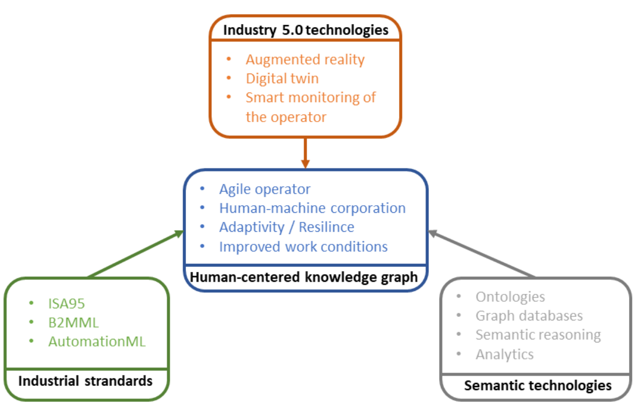

Fig. 1. The proposed design concept for the development of an human-centered knowledge graph

development is the utilisation of standardized models, which allows more efficient integration of a new design concept into a production system, and the expansion of existing methodologies makes the learning period of technical features more dynamic.

Semantic technologies such as ontologies, graph databases, semantic analytics, and reasoning provide an efficient way to process a large number of data from various sources, as the entire data set becomes transparent and accessible [13], [14]. In order to improve the working conditions of operators, different monitoring systems can be used, such as sensor networks , which can capture the movements of the operator or follow the physical conditions of the personnel [15], [16]. Semantic networks and graph-based analytics are recommended to handle the process information, using linked data features.

The *Industry 5.0 technologies* bring pioneer solutions to provide a safer and more comfortable environment for the workers while ensuring access to technologies that enable automation and increase productivity as digital twins and augmented reality or smart monitoring of the operators in the production area. The key enabling technologies of Industry 5.0 are cobots, 6G and beyond, digital twin, blockchain, Internet of Every Thing, big data analytics, edge computing and artificial intelligence [17]. For example, a service or assembly procedure can be facilitated with AR, or production development scenarios can be modeled with a digital twin before re-designing the shopfloor. The novelties of Industry 5.0 research are recommended to facilitate human-machine collaboration, such as AR-aided assembly or creating human digital twins for optimisation purposes.

Finally, thanks to the integration of the introduced three main elements, the *Human-centered knowledge graph* offers effective human-machine collaboration, resilience, agility and improved work conditions for the operator. The knowledge graph includes the monitored information about the activities of the operator, the environment, and all robots and assets which are present in the manufacturing space. By analysing the related knowledge graph data, the collaboration can be improved, the work instructions can be tailored to the worker and any changes that may occur can be handled adaptively.

For a deeper discussion of the problem, an extended MOM (Manufacturing Operations Management) activity model has been investigated, which is visualised in Figure 2, where the elements can be considered according to the time they occur during work execution. The temporal view of the generic activity model as Pre-, Actual-, Post-Work and Reference data is also highlighted [18]. Furthermore, the extension modules of the standard activity model of MOM [19] are visualised in the bottom, with brown color.

The MOM approach aims to show in detail the mechanisms associated with the operator during a general manufacturing activity and focus on the properties of the added monitoring and support framework elements. The generic activity model is divided into four parts based on the temporal view (highlighted with green labels on the figure); therefore, the model is

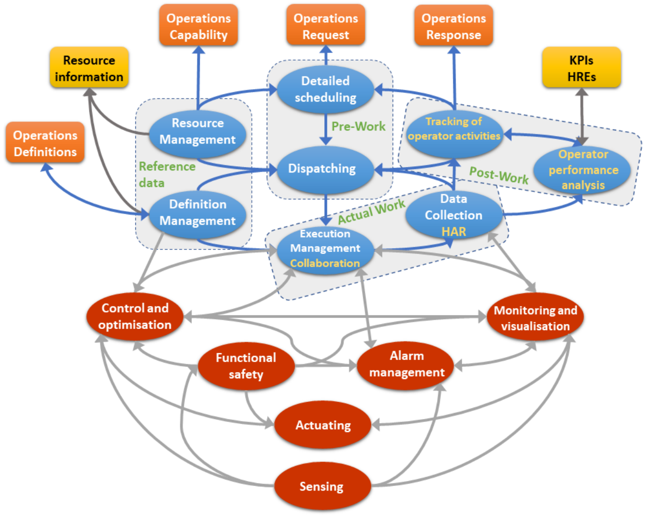

Fig. 2. Activity model of manufacturing operations management with an operator-centric view

analysed and discussed similarly.

The *Reference data* contains all the information about specific operators as capabilities, skills and experience in certain fields. The *Resource* and the *Definition Management* blocks of the MOM store and aggregate this information and determine base data for the following work sections of the model. As an extension to the reference data section, the *Control and optimisation* block is advised, where machine learning [20], [21] or artificial intelligence-based solutions [22] can improve the ongoing production processes.

The second part on Figure 2 is the *Pre-work*, where the *Detailed scheduling* is utilised, based on the *Operations Request* and the *Dispatching* is also performed. These activities manage that all operators have adequate work instructions, scheduling and optimal allocation.

The *Actual-work* section of the MOM describes the activities which are happening in the present, controlled by the *Execution Management*, while *Data Collection* is in progress. Some human-centered aspects are added (with yellow text color), such as *Collaboration* or utilisation of Human Activity Recognition (*HAR*) sensor technologies. The real-time operator support is aimed to be reinforced, therefore, *Alarm management* and *Monitoring and visualisation* are added as extension elements. An alarm management system [23] can prioritise, group and classify the alerts and event notifications used in the supervisory control and data acquisition (SCADA) system, improving performance and monitoring safety. A smart monitoring system can collect data on various manufacturing objects, such as temperature, noise, or vibrations, and obtain them in real life to provide a graphical visualisation and alerts when an abnormality occurs [24]. For example, a high-level visualisation technique can be based on augmented reality that assists the operator with information from the digital twin [25].

Finally, in the *Post-work* period of the activity model the *Tracking of the operator activities* are performed, to get *Operations Response* for the MOM. Furthermore, the *Operator performance analysis* is utilised, which is the source of the KPIs (key performance indicator) and HREs (human resource effectiveness), which are key elements in the knowledge graph to enable resilient and agile conditions for the operators.

The briefly discussed extension modules of the activity model are interconnected to the knowledge graph with semantic technologies. The emerging smart cyber-physical systems create the framework where each human and machine segment of the complex manufacturing system is appropriately monitored and the information systems are interoperable [26], [27].

After discussing the presented Human-centered knowledge graph-based design concept, the following Section continues with the first building block of the approach and investigates the most relevant industry-standard based operator modeling schemas.

III. Building elements of a human-centered knowledge graph

This section summarises the most utilised industrial standards and markup languages, namely: ISA-95, AutomationML and B2MML, which can model the operator in a complex production environment, concentrating on the work performance, human-machine collaboration and job scheduling factors. Furthermore, some research examples are shown about the utilisation of these standards to demonstrate adaptability.

The development trend of system integration in the manufacturing industry is to achieve standardization. ISA-95 [28] is one of the essential standards in the field of enterprise-control system integration and serves a highly utilised basis for design Industry 4.0 [29], IIoT (Industrial Internet of Things) [30] or smart factory [31] related MESs and MOMs. With the motivation to create a semantically integrated design concept, the Production Capability and Personnel model of the ISA-95 standard are advised as a basis for modeling.

Figure 3 shows the UML diagram (Unified Modeling Language) of the Production Capability model (IEC 62264 standard [32]), and the information from sub-classes represents the capability and capability property characteristics of Personnel, Equipment, and Material.

In Figure 4, the Personnel model is represented with a UML, which contains information about the *Class* type of person in the enterprise, such as a production manager or operator; the *Property* as seniority, position, or division; and *Qualification* such as a special task or position of the Personnel.

B2MML is an implementation of IEC/ISO 62264 to provide a freely available XML (Extensible Markup Language) for manufacturing companies [33]. In a standard B2MML model the operator is described as *Person* as an XML schema (XSD), which is an element of the *PersonnelClass*, and extendable with properties, such as *PersonProperty*, *Location*, *PersonType* or *PersonnelCapability*. Furthermore, a *JobOrder* schema element is also can be interlinked in the model with an

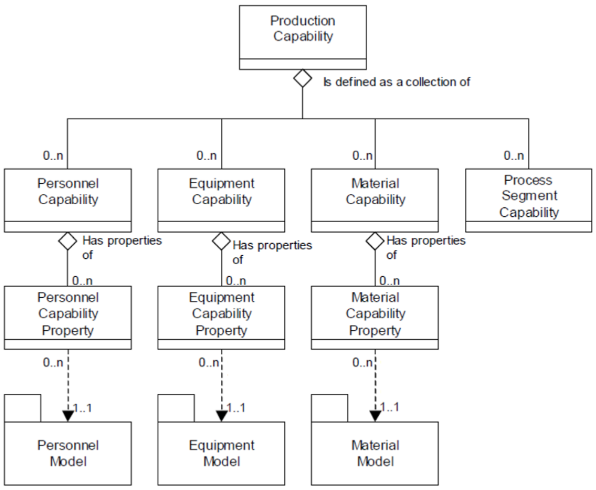

Fig. 3. Production Capability model from ISA-95 [28]

operator, where information as *WorkType*, *Priority*, *Command*, *PersonnelRequirement* or *OperationLocation* can be stored.

AutomationML [34] aims to standardise data exchange in the engineering process of production systems. In an AutomationML environemnt the IEC 62264-2 personnel model [35] offers a method to model the operator in a production process with the following elements: *Personnel Class*, *Personnel Class Property*, *Person* and *Person Property*.

A study proposed a modular framework to create AR-based work instructions [36] with image-based state tracking, using an ISA-95 standard-based ontology, which serves as an example to consider. The different modules of the model are: the *WorkMaster* as the parent data block of the complete assembly, the *WorkflowSpecifications* for the sequence of the tasks that the operator needs to follow, and the *WorkAlerts* in parallel to let the process tracker inform the connected systems (e.g., the AR application) about the current status of the assembly sequence [36].

B2MML standard elements are recommended for developing problem-specific ontologies, as the concept of collaborative assembly workplaces [37], where semantic technologies are utlised to enhance interoperability with external legacy systems such as ERP and MES. The so-called *VAR ontology*

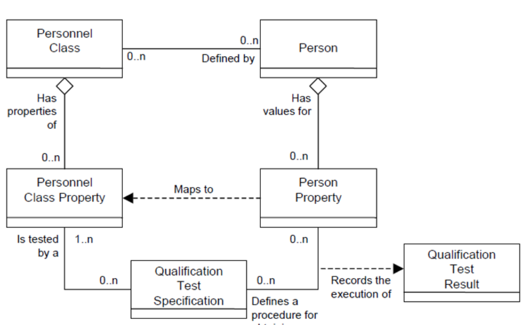

Fig. 4. Personnel model from ISA-95 [28]

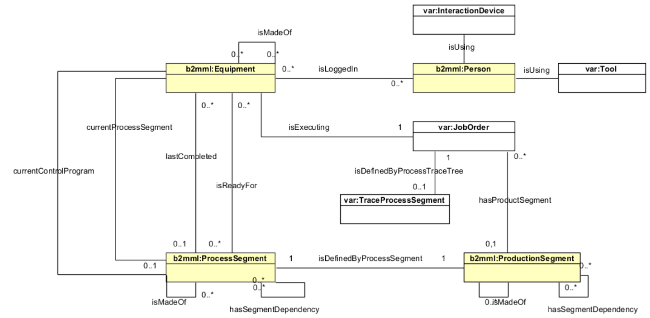

Fig. 5. Implementation of B2MML elements in the Dynamic Actual Status Representation of VAR Ontology [37]

has three main parts, the tangible assets, the intangible assets and the dynamic status, which is visualised with a UML diagram in Figure 5.

AutomationML is also advised for an exchange file format to be a step of automatic workplace design-based on optimised resource allocation [38]. The so-called product-process-resource-triplets (PPR) [39] are created to be a set of appropriate and feasible resources for the assembly steps and the additional product requirements. The creation of the PPR-triplets based on the *workplace*, *products*, *processes* data, which can be stored in AutomationML file format. The mapping information of PPR can assist derive the processes and resources required to manufacture the designed product.

The OWL (Web Ontology Language) representation model of manufacturing data allows to inherit, extend or adapt the semantic description for each component in connection with the operator. Therefore, in the following section, some specific ontological, semantic-based and knowledge graph solutions for operator support are discussed.

IV. Support the Operator with Ontologies and Knowledge Graphs

This section briefly discusses the benefits of semantic solutions in the industry for operator monitoring and support and introduces some applications of ontologies and knowledge graphs. In Sub-section IV-A, HAR with semantic tools are in focus, while, in Sub-section IV-B the collaboration and ergonomics related developments are consider.

Firstly, in Table I some of the main features of utilising semantic technologies and graph analytics are listed in a human-centered approach [40]. These analytical methods can serve a better monitoring and understanding of HRE [41] and KPI [42] factors. Additionally, an application example is given in Table I for each network metrics.

There is a lack of operator-based models, especially in decision-making aspects [43], therefore, integrating the human operator model into the shop floor control system is advised. The facilitation of human-machine interaction with ontologies is recommended, as the UML (based on a *Ref.* [44]) shows in Figure 6, where information about operators is described with three different domain ontologies using the CPS knowledge repositories and the PPR-triplets approach as follows: Product

Network metrics	Analytical features of knowledge graphs
Centrality computation	Which are the critical objects in the network?
	Detect the most significant influencing factors of the operator's environment.
Node and edge similarities	How similar or close are two objects based on their properties and how they are connected with other objects?
	Solve operator resource allocation problems.
Flows and paths	What is the shortest, cheapest, or quickest way to perform a process step?
	Optimise the shop floor layout to align with operator needs.
Cycles	Are there cycles in the graph, and where are they?
	Analyse human and machine task allocation in a collaborative work environment
Network communities	What communities can find in the production network?
	Facilitate the design of human-machine collaboration or cell formation.

TABLE I
KNOWLEDGE GRAPH METRICS AND ANALYTICAL FEATURES

Ontology, Process Ontology, and Resource Ontology. The *Operator* class is connected with *State*, *Skill* and *Schedule* related semantic groups. Furthermore, the *Skill* class of the operator is interlinked to the *Operation* class.

A. Human activity recognition

This subsection proposes some recommendations and examples of applications for HAR solutions for operator support.

The design challenges of a HAR system, proposed by a survey [45] are the followings: (1) selection of attributes and sensors, (2) obtrusiveness, (3) data collection protocol, (4) recognition performance, (5) energy consumption, (6) processing and (7) flexibility. During the development a human-centered knowledge graph, each of these aspects has to be considered. In smart factories, wearable sensors are one of the most emerging technologies, which can be highly utilised for operator support and activity recognition. From the point

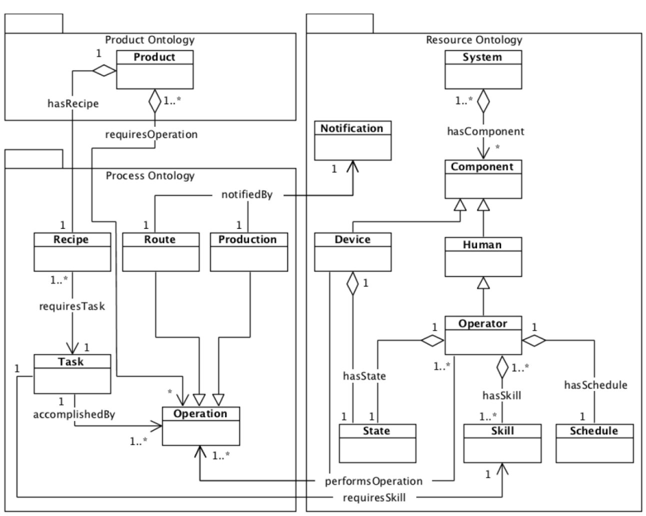

Fig. 6. Structure of an ontology, for Including Human Tasks as Semantic Resources in Manufacturing [44]

of sensor nature, if wearable or external, a HAR system can be online, supervised offline or semi-supervised [45]. Such devices, for example, can be indoor positioning, heart monitor or light sensor.

Different methods and ontologies for human behavior recognition can be classified as data-driven and knowledge-based techniques. The integration of these two methodologies is recommended, as it can help manage limitations in scenarios with several actors, provide semantics to a variety of production activities or worker identification according to behavior semantics [46].

The utilisation of a machine learning-aided approach has been proposed, where online activity recognition and activity discovery are combined in an algorithm [47], and the method identifies patterns in sensor data, which can provide insights on behavior patterns. The approach can be used to identify and correct possible sources of annotation error and, thanks to that, improve the quality of the annotated data.

In semantic-based human activity recognition, one of the most significant feature is to recognise new activities that have not been pre-stored or trained previously in the system. In a research of recognising activities from image and video data with semantic features [48], the activities have been divided into four groups: atomic actions, people interactions, human–object interactions, and group activities. Furthermore, the most popular features of an action should be included in the semantic space, such as the human body and pose, attributes, related objects or scene context.

The structure of a probabilistic ontological framework [49] is visualised in Figure 7, as an application example, where the aim is to recognise multilevel human activities. The method has been utilised to define 86 different *Atomic Gestures* classes, while the users did wear RFID gloves and accelerometers to detect so-called arm functions (such as push, grab or pull) and used objects.

After investigating the human activity recognition solutions suited for the knowledge graph-based design concept, in the

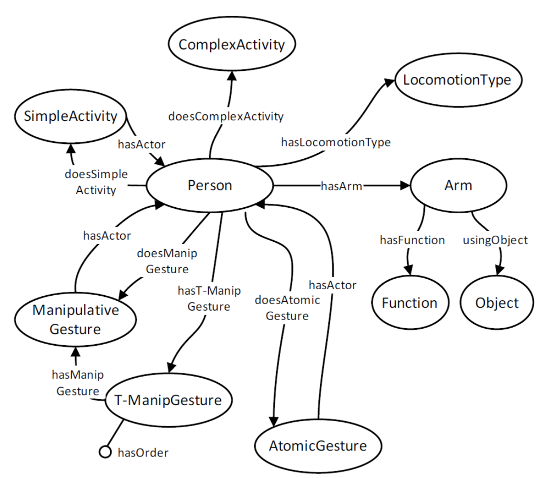

Fig. 7. An ontology-based technique for multilevel activity recognition [49]

following subsection, the support of the operator is discussed from the view of ergonomics and human-machine collaboration.

B. Ergonomics and collaboration

This subsection highlights the importance and benefits of integrating ontologies into a human-centered knowledge graph, which facilitates ergonomics and collaboration in a production environment. As they are utilised in many cases in integration with each other, therefore will be investigated together.

Ontology evolution must be supported through the entire life cycle, with proactive collaboration between knowledge workers and knowledge engineers. The *Human-Centered Ontology Engineering Methodology* [50], following the human-centered approach, highlights integrating ontology engineering environments with knowledge workers practices considerably, enabling knowledge workers to interact directly with their conceptualisations at a high level of abstraction.

The operators must be allowed to easily interact with industrial assets while working on other, more complex ones in an Industry 5.0 environment. To fulfill this development goal, a generic semantic-based task-oriented dialogue system framework as KIDE4I (Knowledge-drIven Dialogue framEwork for Industry) [51] may offer a solution to reduce the cognitive demand. The more processes step can be made easier in production with voice or motion control, the more the procedures can be simplified for the operator, and the more ergonomic work environment can be formed. Additionally, the activity takt times can be shortened thanks to the developed human-machine interaction features.

The ergonomics system can be divided into three subsystems as the human, machine and environment, which is described in Figure 8, with the monitored elements and conditions [52]. Physical load stands for how much manual labor the operator is able to handle without decreasing the work efficiency, while mental load describes the psychological pressure and information processing during work time. In the design of modern production space, it is essential to monitor several factors in the environment, on the machines and devices, and as in the example presented above, to observe as many physical and mental characteristics of the personnel as possible. By embedding these parameters into the knowledge graph, it could be achieved to create efficient human-machine collaboration and more ergonomic workspace, with continuous improvement.

As evidenced by a research [53], there is a need for a multi-ontology approach and the Cynefin Framework [54] is advised to be applied for ergonomics, multiple views and interaction of multiple agents. In this approach four domains are used: the simple, the complex, the complicated and the chaotic, to provide a way of re-perceiving situations where ergonomic related problems can occur or have already been identified. The design of an ergonomic work environment with a multi-ontology methodology could also facilitate human-machine collaboration, as a part of the human-centered knowledge graph-based design concept.

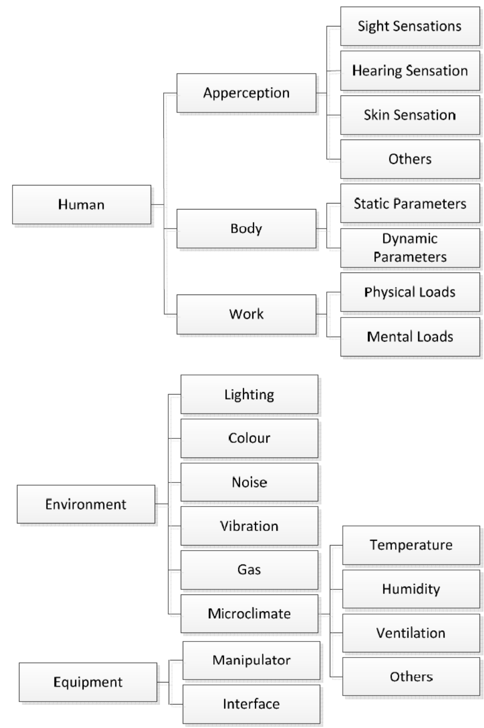

Fig. 8. Mapping framework of human, environment and equipment [52]

This section studied the knowledge graph-based operator support and made recommendations regarding human activity recognition, collaboration, and ergonomics-related aspects. In the following section, the human-centered knowledge graph research is concluded.

V. Conclusion

This paper presents a human-centered knowledge graph-based design concept based on industry standards and semantic technologies associated with Industry 5.0 technologies. The work activities performed by the operator are in the scope, including the evaluation of movements, collaboration with machines, work steps, ergonomics, and other conditions. Additionally, it highlights that activity recognition technologies can enhance the utilisable data in a knowledge graph for a smart factory environment. The inadequate monitoring and support of operators in current industry standards have been highlighted, and the new human-centered approach in modern production has been recommended. In the factory of the future, using knowledge graphs, the entire data collection and knowledge exploration processes will be automated, which can facilitate the support of the human-digital twin and the implementation of Industry 5.0 technologies. This paper aims to summarise the existing methods and tools of ontology development and propose a concept to create standard models for human-centered collaboration. The contributions of this study are the followings:

- Highlight the need of integration human factors in cyber-physical systems

- Suggests the extension of the automation standards (ISA-95, AutomationML, B2MML) with human-related processes
- Present examples of utilisation semantic technologies
- Propose a concept of a human-centered knowledge graph-based design

In future work, the application of the human-centered knowledge graph-based design concept in an intelligent space is planned, to support the design of human-machine and human-human cooperation in manufacturing. The vertices of the knowledge graph can represent events, resources/assets, or competencies, while the edges represent the sets formed according to the activities/cooperations or attribute-type relationships [55]. Based on the simultaneous and integrated monitoring of the activities of the machines, robots, operators, and mobile robots, additional functions [15] that support cooperation can be developed. An ontology-based production simulation [56] is also planned to be developed to perform a case study of a human-centered knowledge graph, where the design concept can be investigated more in-depth. Additionally, the challenge of designing resilient human-machine teams for Industry 5.0 smart manufacturing environments [57] offers many research challenges, which are planned to investigate.

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