AWARE: A Situational Awareness Framework for Facilitating Adaptive Behavior of Autonomous Vehicles in Manufacturing

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Abstract. In this paper, we introduce Aware, a knowledge-enabled framework for robots' situational awareness. It is designed to support autonomous logistics vehicles operating in automobile manufacturing plants. Aware comprises an ontology grounding robots' observations, a knowledge reasoner, and a set of behavioral rules: The Aware ontology models data streams of proprioceptive and exteroceptive sensors into high-level semantic representations. The knowledge reasoner infers adequate policy by reasoning over a sliding window of observations, presumably depicting the robot's perceptions and actual state of knowledge. The behavioral rules, in analogy to road traffic rules and common sense, regulate the operation of autonomous robots in a manufacturing environment despite their obvious peculiarity. Our rules are the first ones facilitating the orderly and timely flow of vehicles. We show the applicability of Aware in an industrial set up. Overall, we posit that situational awareness is a fundamental element towards functional autonomy and argue that it can provide a reliable basis for organizing and controlling robots in a smart factory in the near future.

Keywords: Knowledge graphs · Autonomous vehicles · Semantics-based smart factory · Internet of Things

1 Introduction

A plethora of autonomous and automated guided vehicles[1] are increasingly engaging in logistics operations. With the diversity of autonomous robots such

[1] We use vehicle and robot interchangeably throughout the course of this paper.

This work was supported by BMW Group.

J. Z. Pan et al. (Eds.): ISWC 2020, LNCS 12507, pp. 651–666, 2020.
https://doi.org/10.1007/978-3-030-62466-8_40

as transport robots, autonomous forklifts and autonomous tugger trains, substantial challenges emerge to optimize operations within a smart factory [1]. The German Association of the Automotive Industry published the communication interface VDA5050[2], between automated guided vehicles (AGVs) and a central master controller within the automotive manufacturing plants. VDA5050 enables the implementation of parallel and complementary operations of AGVs through a central master controller. Further, the American National Standards Institute/Industrial Truck Safety Development Foundation released the safety standard ANSI/ITSDF B56.5-2019[3] for driverless, automatically guided industrial vehicles. However, less work has been done towards governing interactions with other agents encountered on the shop floor that are not monitored by the same master controller, such as manned industrial vehicles and autonomous vehicles. In an analogous domain, in road autonomous driving, vehicles' interactions are typically governed by established priors like traffic rules and common sense. However, to the best of our knowledge, such priors over operational conduct of industrial vehicles, besides the safety-related priors [2,3], have not yet been considered in research and standards efforts. Examples of operational priors include right of way or overtaking behavior on divided aisles. Autonomous robots in logistics are currently able to perform complex tasks such as transportation, goods pick up and goods drop off. In a case study on logistics vehicles in an automobile manufacturing plant, we deduce that autonomous vehicles, whereas operating safely without being controlled directly by humans, still lack behavioral grounding. We observe operational impediments caused by: (1) low agility of autonomous vehicles compared to manned vehicles caused by rigorous safety regulations implemented on the autonomous vehicle, (2) autonomous vehicles possibly getting into bottlenecks in various situations such as in intersections, or narrow aisles.

Current autonomous robots are equipped with various sensors like depth cameras, LiDAR, indoor localization tags and ultrasonic sensors. Despite the development of artificial intelligence approaches depicting the streams of data published from the sensors, such as object detection [4] and 3D pose estimation [5], we posit that such representation is not solely sufficient to ensure timely and orderly operation, and must be complemented with situational awareness. Vehicles cannot understand and reason over their environment without a high-level semantic representation of the data. In [6], we introduced the AWARE ontology eliciting the knowledge of the moment as perceived by the autonomous robot, including its telemetry, priors on its environment, its sensed surrounding, and the rules governing the relations between the perceived assets. AWARE was developed in Web Ontology Language (OWL)[4] [7], which is particularly advantageous when reasoning and handling data from heterogeneous data streams. In

[2] VDA5050 – Schnittstelle zur Kommunikation zwischen Fahrerlosen Transportfahrzeugen (FTF) und einer Leitsteuerung, https://www.vda.de/en.

[3] ANSI/ITSDF B56.5-2019 Safety standard for driverless, automatic guided industrial vehicles and automated functions of manned industrial vehicles.

[4] https://www.w3.org/OWL/.

this paper, we introduce the Aware framework to close the gap between the perceptions of the robot and further knowledge processing. Aware represents processed data streams as what we refer to as observations using timestamp-based temporal RDF representation [8]. The Aware decision module uses a set of rules to reason over observations and priors in order to adapt the behavior of the robot. The proposed approach can be easily extended to deal with further situations requiring robots' awareness by adding more rules and adapting the ontology accordingly to cover the application domain. Overall, our main contributions of this paper are:

1. We introduce Aware, a knowledge-enabled framework for robots' reasoning that is, for the first time, specifically designed for enhancing situational awareness of autonomous robots operating in a manufacturing plant. Aware includes an ontology, a set of rules, and a reasoner.
2. We publish the first set of rules governing autonomous logistics vehicles in a manufacturing plant, resolving traffic bottlenecks and facilitating orderly and timely operations within a smart factory.
3. We show the applicability of the Aware ontology to ground robots' proprioceptive and exteroceptive perceptions, as well as priors on the environment, for the purpose of situational awareness.

The remainder of this paper is organized as follows: In Sect. 2, we review work related to the manufacturing domain's ontologies, knowledge processing frameworks, and situational awareness applications. Further, we review impediments we identified by observing operational autonomous robots deployed in a manufacturing environment. Next, in Sect. 3, we introduce the Aware framework. In Sect. 4, we describe how we evaluated the framework and its comprised ontology. We describe the lessons learned from developing an industrial application based on Semantic Web technologies in Sect. 5. We summarize the paper in Sect. 6.

2 Related Work and Priors

In this section, we provide background information about the two areas whose intersection this work resides in: ontologies supporting robotics applications, and knowledge processing frameworks. Then we present work related to situational awareness of autonomous robots and provide insights on impediments observed on the shop floor that can be resolved through situational awareness.

Ontologies. Ontologies have been applied in robotics applications to describe the semantic knowledge of robots. Low-level data streams from sensors are transformed into high-level semantic representations following ontology grounding. Most previous research related to robotics cognition, such as [9–13], adopted knowledge models focused on task planning. In [13], the knowledge schema represents robots' actions and perceptions but does not address knowledge of intrinsic states. Further, [9–11,13] lack the use of common terminologies provided by IEEE 1872 [14], W3C[5] or OGC[6] standards. Moreover, the operational environ-

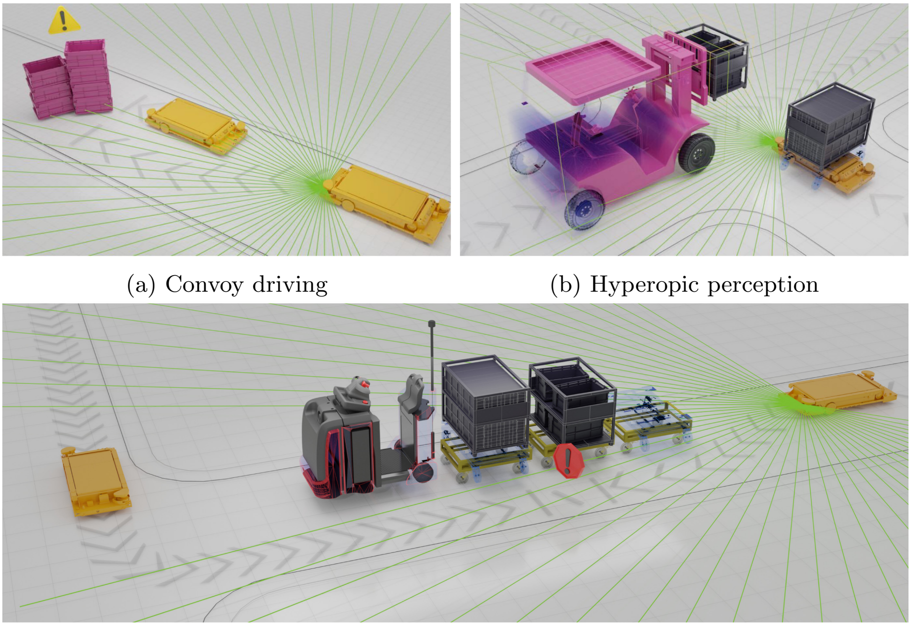
[5] https://www.w3.org/.
[6] https://www.opengeospatial.org/.

ment represented in these knowledge models is not relevant to manufacturing plants. In [6], we introduced the Aware ontology to represent the prevailing state of knowledge of the autonomous robot operating within an automobile manufacturing plant.

Knowledge Processing Frameworks. Ontology-based approaches for robots' autonomy are thoroughly discussed in a recently published review [15]. OMRKF [9] was designed to enable service robots in household environments. The framework enhances the robot's navigation and task planning capabilities. KnowRob [16] also focuses on household environments. Knowledge in KnowRob is organized in an action-centric way to support reasoning about action and task planning. OUR-K [10] is oriented towards robot intelligence for service robot use cases. It builds up rich knowledge for the robot to allow the completion of tasks even if the information at its disposal is incomplete. Open-Robots (ORO) [11] focuses on the implementation of a knowledge representation and reasoning for autonomous robots deployed in complex environments where they need human-machine interaction capabilities. Perception and Manipulation Knowledge (PMK) [12] is an ontological-based reasoning framework to enhance a robot's task- and motion-planning capabilities in the manipulation domain.

Situational Awareness. Situational awareness, as defined in the Oxford dictionary, is knowing that something exists and is important. Endsley [17] defined the scientific term "Situational Awareness" (SA) as the perception of relevant elements in the environment, the comprehension of their significance, and the projection of their future status. Thus, in this context, achieving situational awareness in robotics goes beyond ensuring basic functionalities such as navigation or task planning to decide on the most favorable course of action. Awareness has been essential in a wide range of domains such as urban autonomous driving [18–21] where SA helps to understand the interactions between perceived entities and empowers decision making in traffic situations. In air traffic control [22,23], SA helps ensuring efficiency and safety during take-off and landing by assessing locations of the aircrafts and projecting their future locations. In [24], SA increases cell phone profitableness by improving its functionalities. According to Endsley [17], good SA still does not ensure good performance, however, good performance becomes more likely with SA.

Impediment Situations in Manufacturing Environments. The complexity of manufacturing environments where autonomous robots are deployed is mainly due to their heterogeneity: they comprise both static and moving objects, humans as well as machines, autonomous and non-autonomous vehicles. The complexity is increased by the difficulty of establishing a traffic rule book that regulates the traffic within the manufacturing plant. In a case study conducted on autonomous transport robots deployed in an automobile manufacturing plant, we observe impediments in multiple situations such as at intersections. Although the robots are equipped with the required hardware and software to operate safely without human supervision, their behavior still demonstrates a lack of smoothness due to their shortness in cognition abilities. In Fig. 1, we illustrate



(a) Convoy driving

(b) Hyperopic perception

(c) Oncoming traffic with long obstacle

Fig. 1. Pictures of impediments encountered in a case study on autonomous robots deployed in an automobile manufacturing plant.

some operational drawbacks encountered on the shop floor case study. These drawbacks are illustrated to motivate the necessity of situational awareness for a functional autonomy: In a convoy driving situation, as shown in Fig. 1a, a desired behavior for the rear robot is to mimic the behavioral pattern of the front robot, without attempting to overtake, since the latter has an anticipated insight and thus a more reliable judgment. In Fig. 1b, the field of view of the autonomous robot is deficient because of proximity. The autonomous robot is required to perceive the loaded forklift while approaching and to reason and deduce potential collision of loads in order to increase separation distance. In Fig. 1c, overtaking an obstacle on a two-ways aisle might lead to a bottleneck with oncoming traffic. A more suited behavior is to avoid overtaking long obstacles.

3 AWARE: Situational Awareness Framework

AWARE is the first situational awareness framework specifically conceived for the purpose of augmenting autonomous robots in automobile manufacturing plants with awareness capabilities. The framework can be easily extended to support other applications of autonomous vehicles. In the following, we present the AWARE knowledge schema, the AWARE knowledge base, the cognitive abilities expressed through behavioral rules, and the ontology-based decision-making system.

3.1 Knowledge Schema

According to the AWARE ontology[7] [6], low-level information is represented by a format understandable to both humans and machines. The AWARE ontology includes 91 classes. In this section, we detail the main elements of the ontology: the environment model, the robot perceptions, and the decisions the robot is allowed to make.

Environment Model. The environment model represents the spatial setting where the autonomous robot operates. It includes a high-level representation of the manufacturing plant, its assets, and the relations between the assets. The environment assets are represented in classes for different moving objects as well as classes for topographic areas and zones that do not change over time.

Perceptions. The perceptions schema captures knowledge about the state of the autonomous robot and the state of the surrounding assets. Both extrinsic sensors' data streams and intrinsic signals are represented. Knowledge about the surrounding assets is modeled using the class *Observation*. An observation instance is used to link all elements of a perception: (1) the observed element, (2) its observed property, (3) the sensor that made the observation, (4) the procedure or algorithm used to extract the property, and (5) the timestamp of the observation. The classes *TransitwayObstacle* and *ObjectOfFocus* are used to identify objects that are of particular relevance in the robot's field of focus. It is out of the scope of this paper to detail the AWARE data acquisition module and the related fields of focus. The class *TransitwayObstacle* is used to describe objects treated as obstacles to be avoided by the robot. *ObjectOfFocus* indicates objects perceived by the camera within the robot's field of focus, that may represent an obstacle in the future.

3.2 Knowledge Base

Apart from the ontology, we create a knowledge base (KB) containing instances of the concepts in our ontology. Our knowledge base contains both time-invariant instances and instances that do vary over time. As time-invariant instances we have instances of the class *Decision*, such as *pause*, *adjustSafetyRange*, and instances of the class *Procedure*, such as object detection models like *YOLO* [25] or *DetectNet* [4]. Furthermore, instances of the class *OperationalArea* and of the class *ConstraintZone* are time-invariant. *OperationalArea* represents parts of the plant with a particular functionality such as aisles or drop-off areas, while

[7] https://w3id.org/AWARE/ontology.

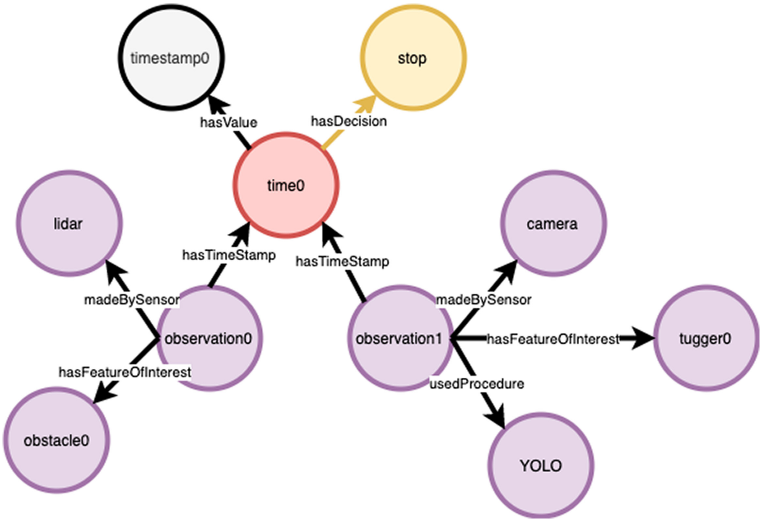


Fig. 2. Observations modeled in a knowledge base.

the class *ConstraintZone* refers to delimited surfaces in the plant where specific behavioral regulations apply such as zones with limited speed or limited capacity zones. Time-variant instances are characterized by a timestamp. They represent processed data from different intrinsic and extrinsic sensor streams. Data extracted from the autonomous robot's internal state and its surrounding environment is inserted into the KB as instances of the class *Observation*. An example of two instances from class *Observation* is shown in Fig. 2. One observation is concerned with one feature of interest only. Multiple observations can be characterized by the same timestamp. If multiple features of interest appear simultaneously, such as multiple detections within a single frame, an observation is created for each independently.

3.3 Basic Assumptions

AWARE reasons over behavioral rules to enhance the performance of autonomous transport robots. To the best of our knowledge, unlike in road traffic, the functioning of autonomous vehicles in closed environments is not standardized by an established code of conduct. No published standard regulates traffic within a manufacturing plant, such as intersections right of way or rules on when an autonomous vehicle is supposed to yield way. Nevertheless, autonomous robots are able to safely perform complex tasks without human intervention. The observed right of way allocation is often following a first-come first-served basis, or an it-fits-I-pass policy. We set forth the need to introduce behavioral rules to govern the behavior of autonomous vehicles deployed in a production environment, similarly to the implemented safety regulations [2,3]. In the following, we present our basic assumptions for the behavioral rules guiding vehicles in a manufacturing environment. We derived these assumptions from the observed impediments encountered on productive autonomous transport robots. We list these assumptions to outline the peculiarities of agents' situational awareness and its modeling.

1. The behavioral rules are not considered as safety rules and are not intended to replace such; instead, our rules are designed to ensure timely and orderly operations of the smart factory, where humans, manned vehicles, and autonomous vehicles are required to function in alignment.
2. Situational awareness is not a control system; instead, it is a guidance system facilitating the behavior adaptation of *autonomous* robots. Hence, in the absence of guidance, the robot is supposed to proceed as indicated by its state machine.
3. The autonomous vehicle has always lower priority of way facing manned vehicles. This is due to the reduced agility of autonomous vehicles compared to manned vehicles.
4. Autonomous vehicles interact with each other following right of way rules similar to road traffic rules. That requires the ability for autonomous vehicles to recognize other autonomous vehicles and differentiate them from manned vehicles.
5. All autonomous vehicles deployed in the same operations environment are expected to follow the same traffic rules.
6. All autonomous vehicles deployed in the same operations environment are expected to have the same priors on the environment. Priors examples are intersections, driveway side, main and secondary aisles.
7. Autonomous vehicles cannot communicate between each others. To the best of our knowledge, no standard has been published to enforce lateral communication between autonomous vehicles. Thus, we do not enforce that constraint to solve eventual traffic congestion. Aware identifies unsolvable congestions and notifies the cloud master controller. We predicate the need for such standardized vehicle-to-vehicle communication to guarantee a complete autonomy.

3.4 AWARE Architecture

The decision making system is built on top of the knowledge base schema enriched by a set of behavioral rules. Reasoning over the statements in the knowledge base, the robot adapts its behavior and avoids different bottleneck situations by applying the inferred decisions such as 'pause' or 'increaseSafetyRange'. An architecture diagram of the framework is shown in Fig. 3. In the following, we outline the components of the architecture in more detail.

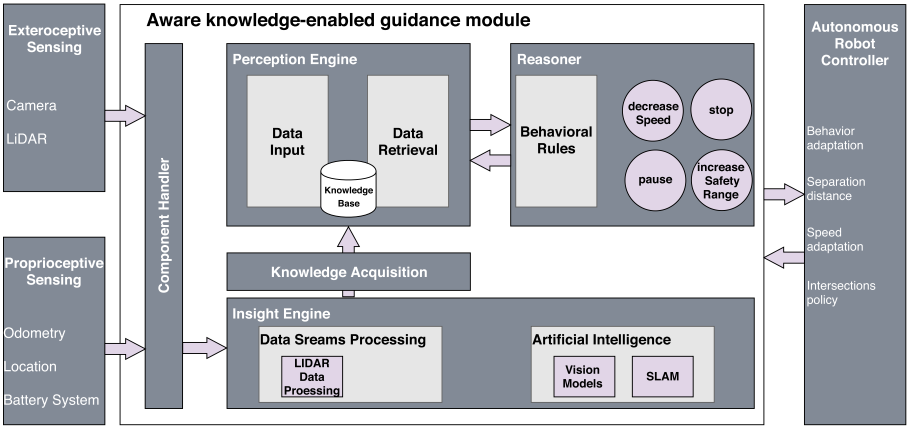


Fig. 3. An overview of the AWARE architecture.

Component Handler. The component handler is the data extraction module, adapting frame rate of data streams, and ensuring alignment of data and timestamps.

Insight Engine. The insights engine is the central data processing component through artificial intelligence, and diverse and redundant data analysis processes. Thus, real-world knowledge extracted by the Components Handler is structured according to the ontology. For example, images captured by the camera are fed to a trained neural network for object detection.

Knowledge Acquisition. The knowledge acquisition layer applies masks on the processed data to narrow down the insights to the area of focus. The area of focus varies with every sensor: for camera input for example, we filter out detected objects following a trapezium of interest as in [26].

Perception Engine. The perception engine handles data input and data retrieval into and from the knowledge base. This module manages a time window of observations in memory.

Reasoner. On knowledge insertion, a rule written in Prolog [27] automatically checks all the defined behavioral rules to trigger the ones that match the current instantiated state. Depending on the observations in the time window, the inferred guidance is published to the control system to adapt the ego's behavior according to the perceived environment.

Table 1. Subset of rules written in SWRL

Convoy driving
$Observation(?obs) \wedge madeBySensor(?obs, camera)$ $\wedge hasFeatureOfInterest(?obs, ?obj) \wedge STR(?obj)$ $\wedge ObjectOfFocus(?obj) \wedge TransitWayObstacle(?obj)$ $\wedge hasTimeStamp(?obs, ?time) \wedge TemporalEntity(?time)$ $\rightarrow hasDecision(?time, stop)$
Overtaking tugger train with oncoming traffic
$Observation(?obs) \wedge madeBySensor(?obs, camera)$ $\wedge hasFeatureOfInterest(?obs, ?obj) \wedge Tugger(?obj)$ $\wedge ObjectOfFocus(?obj) \wedge hasTimeStamp(?obs, ?time)$ $\wedge TemporalEntity(?time)$ $\rightarrow hasDecision(?time, stop)$
Hyperopic perception
$isLoaded(ego, True) \wedge Observation(?obs)$ $\wedge madeBySensor(?obs, camera) \wedge hasFeatureOfInterest(?obs, ?obj)$ $\wedge Forklift(?obj) \wedge ObjectOfFocus(?obj)$ $\wedge hasTimeStamp(?obs, ?time) \wedge TemporalEntity(?time)$ $\rightarrow hasDecision(?time, increaseSafetyRange)$

3.5 AWARE Implementation

We developed the ontology with the latest version of the Web Ontology Language OWL2 using Protégé, a free open-source ontology editor developed by Stanford[8]. Despite their simplicity, SWRL rules have the disadvantage of being computationally expensive when reasoning over a large number of rules [20]. Hence, we implemented ontology and rules in SWI-Prolog[9] [28], which is a computational effective logic programming language. We store both the ontology and the rules using Prolog [27]. We load the knowledge schema, represented in RDF triples in .owl format, into the konwledge base (KB) of Prolog. The reasoner inspects the data available in the KB and checks it over the rules in order to infer the best course of action following the prevailing situation. We continuously update the KB to keep a 1-minute-duration of knowledge history. We store observations and inferences over a window of time in order to ensure a smooth decision making and filter out erroneous decisions generated by noisy data. The rules, defined in Prolog language, are stored in .pl format. In Table 1, for the sake of expressiveness, we show the rules in SWRL corresponding to the impediments illustrated in Fig. 1.

[8] https://protege.stanford.edu/.
[9] https://www.swi-prolog.org/.

4 Evaluation

Evaluating a knowledge processing framework for situational awareness and behavior adaptation of autonomous vehicles is not a trivial task. The reason behind such challenge is that no evaluation methods or benchmarks are established so far as it is the case in other areas of artificial intelligence research. To assess our framework, we perform a quantitative evaluation by measuring its scalability and responsiveness, and we perform a qualitative evaluation by testing our system on various scenarios.

Quantitative Evaluation. We evaluate the framework's performance by measuring the scalability and the responsiveness. Specifically, we evaluate scalability by computing the time consumed to store a set of RDF triples resulting from observations. We wrote a test script to generate up to 45,000 mock observations from different data streams in a loop, which resulted in 497,104 RDF triples in total. We measure the responsiveness by evaluating the inference time of 200 randomly-generated rules over the RDF triples. All the measurements have been taken on an Intel(R) Core(TM) i7-8565U with a speed 1.80 GHz and 16.0 GB of RAM.

We report the results of our evaluation in Fig. 4. The time consumed scales linearly with the number of generated observations to reach 2.45 s for 45,000 observations. The response time remains almost constant. The reduced response time is due to the optimization of the rules' structure that accelerates the querying process. These results demonstrate that a reasonable amount of knowledge, as expected in the Aware observations time window, can be stored and processed efficiently by our framework. The scalability of the system is currently limited to what a single machine can handle. Overall, the framework's capability for responsiveness appears to be sufficient for modeling situational awareness.

Qualitative Evaluation. To evaluate Aware qualitatively, competency situations were implemented in a simulation environment using the Unity[10] game engine. We collected competency situations by analyzing the behavior of autonomous transport robots deployed in automobile manufacturing plants. We documented the behavior of the deployed robots via onsite observations and expert feedback in three production manufacturing plants in Germany. The observed fleet of deployed autonomous transport robots comprises 100 robots operating during two 8-hour-shifts per day. The study to collect the competency situations was conducted over 10 months.

In Table 2, we list the situations encountered by the autonomous robot that we refer to as *Ego* vehicle, and the corresponding guidance output. For example, on intersections, referred to as *crossingArea*, a desired behavior of autonomous robots is to yield way to manned vehicles. In such case Aware would return a *stop* guidance. Our qualitative evaluation was conducted in an iterative manner

[10] https://unity.com/.

Table 2. List of competency situations and expected output of Aware

Situation	Aware guidance
Ego vehicle is located in a *CrossingArea*	*decreaseSpeed*
Ego vehicle is on *MainAisle* in a *CrossingArea* and detects a manned vehicle in field of focus	*stop*
Ego vehicle is on *MainAisle* in a *CrossingArea* and is driving *straight*	-
Ego vehicle is on *MainAisle* in a *CrossingArea* and is turning *right*	-
Ego vehicle is on *MainAisle* in a *CrossingArea* and is turning *left*. Ego vehicle detects an autonomous vehicle on the opposite *lane* in field of focus	*pause*
Ego vehicle is in a *CrossingArea* with *Decision* of previous timestamp is *pause* and the detected autonomous vehicle on the opposite *lane* in field of focus is stationary	-
Ego vehicle is on *MainAisle* in a *CrossingArea* and is turning *left* Ego vehicle does not encounter an autonomous vehicle on the opposite *lane* in field of focus	-
Ego vehicle is on *SecondaryAisle* in a *CrossingArea* and detects a manned vehicle in field of focus	*stop*
Ego vehicle is on *SecondaryAisle* in a *CrossingArea* while *MainAisle* is not clear	*stop*
Ego vehicle is on *SecondaryAisle* in a *CrossingArea* and is driving *straight* while *MainAisle* is clear	-
Ego vehicle is on *SecondaryAisle* in a *CrossingArea* and is turning *left*. Ego vehicle detects an autonomous vehicle in field of focus	*stop*
Ego vehicle is on *SecondaryAisle* in a *CrossingArea* and is turning *left*	-
Ego vehicle is on *SecondaryAisle* in a *CrossingArea* and is turning *right* while left *Aisle* is clear	-
Ego vehicle is in a *TwoWayAisle* and detects a *Tugger* as *ObjectOfFocus*	*stop*
Ego vehicle is in a *CrossingArea* and detects a *TransitwayObstacle*	*stop*
Ego vehicle detected in the last timestamp a manned vehicle as a *TransitwayObstacle* and enabled obstacle avoidance. Ego vehicle detects another *Entity* as a *ObjectOfFocus* in the field of focus	*stop*
Ego vehicle detects an autonomous vehicle as a *TransitwayObstacle* and as a *ObjectOfFocus*	*stop*
Ego vehicle detects a *Forklift* as a *ObjectOfFocus*	*increaseSafetyRange*

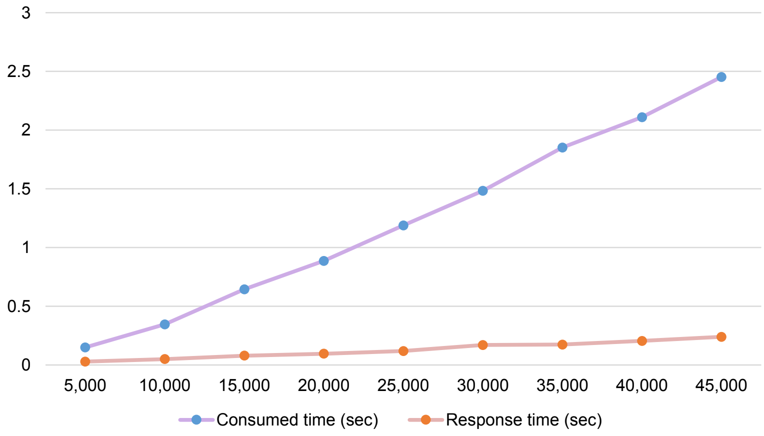


Fig. 4. Scalability and responsiveness per number of observations

during the ontology and framework development process in order to identify missing terms in the ontology and to ensure that AWARE satisfies all competency situations in the end. Evaluating the framework also next to the framework development significantly helped the AWARE ontology and framework to become mature.

5 Lessons Learned

The adoption of semantic technologies in industrial robotics applications is still facing the challenge of bridging the gap between robotics and semantics disciplines. We observed that, heretofore, the impact made by semantic technologies in robotics is limited in industry. Established productive robotics solutions, including route planning, task planning, and manipulation problems, use traditional optimization approaches. Through the work presented in this paper, we pave the way for a productive application of semantic technologies to enhance operations of autonomous robots. For example, the ability to dynamically adapt behavior of the robot has always been a requested feature reported by onsite robots fleet operators to avoid bottlenecks in ways seeming trivial to the human operators. Human operators have priors from road traffic rules, and expect robots to operate similarly. Also, drivers of manned vehicles on the shop floor request that autonomous robots avoid overtaking them. Such behavioral adaptation requires understanding and reasoning capabilities, besides knowledge acquisition and storage.

Knowledge acquisition is challenging for modalities like images where low-level pixels data need to be interpreted into world concepts: to recognise encountered agents through computer vision, a labeled dataset of all possible assets on the shop floor is required, similarly to existing benchmarks for roads autonomous driving [29]. As a result of this work, an object detection images dataset was collected and labeled to train object detection models to recognize and detect assets encountered in manufacturing plants.

It is planned that a pilot Aware robot fleet is deployed in a productive environment of car manufacturing in autumn 2020. Hence, a policy for bringing awareness to autonomous machine was clearly identified as crucial. Overall, we have observed the following practical findings from our study:

1. Creating an ontology is doable, but requires good communication and best practices. Besides a systematic approach to avoid redundant work and to eliminate design errors, it was crucial to us to consider Internet of Things-related peculiarities which have been addressed in ontology engineering only to a limited degree so far. Specifically, we paid attention to (a) *perception* (i.e., how to establish a connection to the world), (b) *intersubjectivity* (i.e., how to align world representations), and (c) the *dynamics* of world knowledge (i.e., how to model events). For more information about these aspects, we can refer to [30].
2. Reasoning based on a rule-engine and an ontology has been applied in various scenarios. In the light of having a well-functioning and scalable Internet of Things scenario, using RDF triples and Prolog turned out to be a valid choice.
3. Rules need to be created by domain experts in order to cover all situations sufficiently. Also, time- and location-related constraints need to be taken into account. For instance, similar to varying traffic rules from country to country, robots operating in one environment (e.g., plant A) might need to cope with different observations and rules in another environment (e.g., plant B).
4. Deploying the framework in production also requires robust knowledge acquisition components adapted to the robots' sensors. In the case of diverse AI solutions, labeled datasets are needed (e.g., for object detection). This aspect should not be underestimated.

6 Conclusion and Prospects

In this paper, we introduced Aware, a situational awareness framework adapted to the perception of autonomous robots operating in automobile production intralogistics. Aware is the first knowledge-enabled framework designed to advance robot cognition within manufacturing environments. Aware incorporates an ontology, a knowledge reasoner, and behavioral rules. The presented knowledge schema integrates proprioceptive and exteroceptive observations. Thus, Aware models the intrinsic and extrinsic perceptions, framing low-level multi-dimensional data streams into high-level semantic representations. Furthermore, the knowledge reasoner provides guidance to the robot state machine based on the set of rules governing the interaction of autonomous robots with other agents operating in the same closed manufacturing environment. We predicate the lack of standards towards managing traffic within a smart factory, since only safety-related priors have been considered in research and standardization efforts so far.

Our future work orientations are two-fold: first, we will develop late fusion components to enable sensor fusion at the knowledge representation level. Therefore, for example, single objects detected by LiDAR as *TransitWayObstacle* and by camera as *ObjectOfFocus* will have their respective *Observation* entries linked to the same feature of interest. Secondly, we will focus on modeling projected future observations based on the observations recorded in a given time window. Ultimately, such projections will enable autonomous robots to distinguish between approaching and receding vehicles.

References

1. Wang, S., Wan, J., Li, D., Zhang, C.: Implementing smart factory of industrie 4.0: an outlook. Int. J. Distrib. Sensor Netw. **12**(1), 3159805:1–3159805:10 (2016)
2. DIN, E.: 1525, Safety of Industrial trucks-Driverless Trucks and their Systems, vol. 12. Beuth-Verlag, Berlin (1998)
3. ANSI/ITSDF: B56.5: 2019, Safety Standard for Driverless, Automatic Guided Industrial Vehicles and Automated Functions of Manned Industrial Vehicles EFFECTIVE. Accessed 08 Dec 2020
4. Tao, A., Barker, J., Sarathy, S.: DetectNet: deep neural network for object detection in DIGITS. Parallel Forall **4**, 1–8 (2016). https://devblogs.nvidia.com/parallelforall/detectnet-deep-neural-network-object-detection-digits/
5. Sundermeyer, M., Marton, Z.-C., Durner, M., Brucker, M., Triebel, R.: Implicit 3D orientation learning for 6D object detection from RGB images. In: Ferrari, V., Hebert, M., Sminchisescu, C., Weiss, Y. (eds.) ECCV 2018. LNCS, vol. 11210, pp. 712–729. Springer, Cham (2018). https://doi.org/10.1007/978-3-030-01231-1_43
6. El Asmar, B., Chelly, S., Färber, M.: AWARE: An Ontology for Situational Awareness of Autonomous Vehicles in Manufacturing. (2020) https://people.aifb.kit.edu/mfa/AWARE/AWARE-Ontology.pdf
7. Welty, C., McGuinness, D.L., Smith, M.K.: OWL Web Ontology Language Guide. W3C recommendation, W3C, February 2004. http://www.w3.org/TR/2004/REC-owl-guide-20040210
8. Gutierrez, C., Hurtado, C.A., Vaisman, A.: Introducing time into RDF. IEEE Trans. Knowl. Data Eng. **19**(2), 207–218 (2006)
9. Suh, I.H., Lim, G.H., Hwang, W., Suh, H., Choi, J.H., Park, Y.T.: Ontology-based multi-layered robot knowledge framework (OMRKF) for robot intelligence. In: 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 429–436. IEEE (2007)
10. Lim, G.H., Suh, I.H., Suh, H.: Ontology-based unified robot knowledge for service robots in indoor environments. IEEE Trans. Syst. Man Cybern.-Part A: Syst. Hum. **41**(3), 492–509 (2010)
11. Lemaignan, S., Ros, R., Mösenlechner, L., Alami, R., Beetz, M.: ORO, a knowledge management platform for cognitive architectures in robotics. In: 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 3548–3553. IEEE (2010)
12. Diab, M., Akbari, A., Ud Din, M., Rosell, J.: PMK-A knowledge processing framework for autonomous robotics perception and manipulation. Sensors **19**(5), 1166 (2019)

13. Beetz, M., Beßler, D., Haidu, A., Pomarlan, M., Bozcuoğlu, A.K., Bartels, G.: Know Rob 2.0 - a 2nd generation knowledge processing framework for cognition-enabled robotic agents. In: 2018 IEEE International Conference on Robotics and Automation (ICRA), pp. 512–519. IEEE (2018)
14. IEEE Robotics and Automation Society: IEEE standard ontologies for robotics and automation. IEEE Stan. **1872–2015**, 1–60 (2015)
15. Olivares-Alarcos, A., et al.: A review and comparison of ontology-based approaches to robot autonomy. Knowl. Eng. Rev. **34**, e29 (2019)
16. Tenorth, M., Beetz, M.: KNOWROB–knowledge processing for autonomous personal robots. In: 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 4261–4266. IEEE (2009)
17. Endsley, M.R.: Toward a theory of situation awareness in dynamic systems. Hum. Factors **37**(1), 32–64 (1995)
18. Wardziński, A.: The role of situation awareness in assuring safety of autonomous vehicles. In: Górski, J. (ed.) SAFECOMP 2006. LNCS, vol. 4166, pp. 205–218. Springer, Heidelberg (2006). https://doi.org/10.1007/11875567_16
19. Buechel, M., Hinz, G., Ruehl, F., Schroth, H., Gyoeri, C., Knoll, A.: Ontology-based traffic scene modeling, traffic regulations dependent situational awareness and decision-making for automated vehicles. In: 2017 IEEE Intelligent Vehicles Symposium (IV), pp. 1471–1476. IEEE (2017)
20. Armand, A., Filliat, D., Ibañez-Guzman, J.: Ontology-based context awareness for driving assistance systems. In: 2014 IEEE intelligent vehicles symposium proceedings, pp. 227–233. IEEE (2014)
21. McAree, O., Aitken, J.M., Veres, S.M.: Towards artificial situation awareness by autonomous vehicles. IFAC-PapersOnLine **50**(1), 7038–7043 (2017)
22. Endsley, M.R., Smolensky, M.W.: Situation Awareness in Air Traffic Control: The Picture. Academic Press, Cambridge (1998)
23. Hagemann, T., Weber, P.: Situational awareness in air traffic management (ATM). Hum. Factors Aerosp. Saf. **3**, 237–243 (2003)
24. Siewiorek, D.P., et al.: SenSay: a context-aware mobile phone. In: 7th International Symposium on Wearable Computers (ISWC 2003), pp. 248–249 (2003)
25. Redmon, J., Divvala, S., Girshick, R., Farhadi, A.: You only look once: unified, real-time object detection. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 779–788 (2016)
26. Tapu, R., Mocanu, B., Zaharia, T.: DEEP-SEE: joint object detection, tracking and recognition with application to visually impaired navigational assistance. Sensors **17**(11), 2473 (2017)
27. Bratko, I.: Prolog Programming for Artificial Intelligence. Pearson Education, London (2001)
28. Wielemaker, J., Schrijvers, T., Triska, M., Lager, T.: SWI-Prolog. Theor. Pract. Logic Program. **12**(1–2), 67–96 (2012)
29. Geiger, A., Lenz, P., Stiller, C., Urtasun, R.: Vision meets robotics: the KITTI dataset. The Int. J. Rob. Res. **32**(11), 1231–1237 (2013)
30. Färber, M., Svetashova, Y., Harth, A.: Theories of meaning for the Internet of Things. In: Bechberger, L., Kühnberger, K.U., Liu, M. (eds.) Concepts in Action - Representation, Learning and Application. Springer (2020)