AWARE: An Ontology for Situational Awareness of Autonomous Vehicles in Manufacturing

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Abstract

With the development of autonomous vehicles, recent research focuses on semantically representing robotic proprioceptive and exteroceptive perceptions (i.e., perception of the own body and of an external world). Such semantic representation is queried by reasoning systems to achieve what we would refer to as *machine awareness*. This aligns with the general purpose of artificial intelligence to utilize commonsense knowledge, but rather relates to the knowledge representation and knowledge elicitation aspects. In this work, we present our ontology for representing background knowledge grounding cognition capabilities of autonomous transport robots. Also, existing ontologies in the domain of robotics and Internet of Things are integrated. We then demonstrate the applicability and extensibility of our ontology to autonomous and automated vehicles implemented in an automobile manufacturing plant. Our robotic situational awareness ontology can provide a basis for organizing and controlling robots in a smart factory in the near future and showcases how situational awareness facilitates the coexistence of smart autonomous agents.

1 Introduction

Logistics processes are increasingly relying on autonomous robots as key component of the automated flow of material within manufacturing plants. Such autonomous robots operating in a complex environment surrounded by manned and autonomous vehicles require commonsense knowledge and the ability to reason over prevailing and predicted future situations (El Asmar et al. 2020). Such ability, that we refer to as *Situational Awareness* (SA) is necessary in the age of the industry 4.0 (Lasi et al. 2014) to ensure timely and orderly operation of autonomous robots. Concurrently, as posited in (El Asmar et al. 2020) SA is not to be conceived as a control system nor as a safety 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. Overall, we argue that *situational awareness* is an essential cornerstone in order to facilitate the autonomous action and interaction of machines.

In the past, the scientific term *Situational Awareness* was defined by Endsley (1995) as the perception of relevant elements in the environment, the comprehension of their significance, and the projection of their future status. In computer science, such world/environment knowledge representation is commonly referred to as commonsense. According to Tandon (2016), commonsense includes (1) properties of objects, (2) relationships between objects, and (3) interactions between objects. In robotics cognition, according to Freedman and Adams (2009), increasing commonsense levels is a viable approach to achieving high levels of robotic situational awareness since robots must possess a comprehensive collection of skills and knowledge, spanning vision processing, logical reasoning, analogical reasoning, and social conventions to perform complex real-time tasks. Furthermore, in (El Asmar et al. 2020), we show impediments encountered during operations of autonomous robots lacking commonsense knowledge, and introduce the AWARE knowledge-enabled framework for situational awareness to guide behavior of autonomous transport robots in an automobile manufacturing plant. However, existing modeling languages, such as ontologies, lack the ability to incorporate machine's *awareness* and, thus, to combine general world *knowledge* (i.e., theories about the world; "understanding and reasoning") with immediate *perception* of the world (Färber, Svetashova, and Harth 2021).

In an analogous domain, in road autonomous driving, vehicles' interactions are typically governed by established priors such as traffic rules and drivers' commonsense. Consequently, based on those priors, considerable research efforts in autonomous driving are directed towards developing reasoners and knowledge models representing a vehicle's and a driver's observations and the dynamics of the surrounding environment (Morignot and Nashashibi 2012; Xiong, Dixit, and Waller 2016; Fernandez et al. 2016; Buechel et al. 2017; Geng et al. 2017; Zhao et al. 2017; Wolf et al. 2019; Huang et al. 2019).

*This work was supported by BMW Group

However, to the best of our knowledge, such established rules do not exist for autonomous robots in intra-logistics. This is due to the fact that, until recently, goods and material movement mainly relied on manned vehicles, where operators resort to commonsense to navigate the vehicles on the factory premises, and are not accountable to liability and legal measures like it is the case on the streets. In this paper we introduce the AWARE knowledge schema (i.e., ontology) facilitating a grounding of machines' perceptions (Harnad 1999) and machines' raw data streams, and, thus, an automated reasoning based on high-level representations. AWARE elicits the knowledge of the moment as perceived by the machine – in our use case, a robot –, including its telemetry, the actual state of its master control system, its sensed surrounding, and the rules governing the relations between the perceived assets. By structuring and interlinking machines' data streams from exteroceptive and proprioceptive sensing (i.e., perception of the own body and of an external world), these streams are deciphered into observations processed by the robot to adapt its behavior according to operational priors.

We thereafter discuss and evaluate the applicability of AWARE in automobile manufacturing plants. AWARE is developed in standard formats following best practices for publishing ontologies (IEEE 2015).

Overall, the main contributions of this paper are as follows:

1. We propose the AWARE ontology, available online at https://w3id.org/AWARE/ontology, for modeling situational awareness. Our ontology combines the representation of the environment, the robot perceptions, and the decisions the robot is allowed to make.
2. Based on an evaluation, we show the coverage and applicability of the AWARE ontology to automobile manufacturing environment.

The rest of this paper is structured as follows: In Section 2, we discuss related ontologies and their limitations, before introducing the developed ontology in Section 3. Section 4 explains how the knowledge graph is applied in our scenario. In Section 5 we describe how we evaluated the ontology. We summarize the paper in Section 6.

2 Related Work

Modeling situational awareness for machines. Although situational awareness is a prominent concept within human factors community, it is rarely used in robotics. Dahn, Fuchs, and Gross (2018) present an application-agnostic definition of the terminology and the processes involved in acquiring Situation Awareness. According to Dahn, Fuchs, and Gross (2018), an agent is situation aware, given a goal and a situation, if it can build a complete representation before the situation evolves. Also, previous research related to robotics cognition and situational awareness, such as (Suh, Lim et al. 2007; Lim, Suh, and Suh 2010; Lemaignan et al. 2010; Diab et al. 2019; Beetz et al. 2018), adopted knowledge models focused on task planning, which does not require a foundational modeling of agents' awareness. In (Beetz et al. 2018), for instance, the knowledge is rather organized in an action-centric way to facilitate manipulation tasks. Furthermore, (Suh, Lim et al. 2007; Lim, Suh, and Suh 2010; Lemaignan et al. 2010; Beetz et al. 2018) lack the use of common terminologies, such as the ones provided by IEEE 1872 (IEEE 2015), W3C[1] or OGC[2]. Apart from the fact that the operational environment represented in these knowledge models is not relevant to manufacturing plants. Komma, Jain, and Mehta (2012) presented a domain-specific ontology for modeling shop floors with autonomous and automated vehicles. However, it only focuses on the communication in a simulation scenario and does not model robots' perception.

Awareness-related ontologies. Several ontologies have been proposed modeling awareness-related aspects, such as sensor information, without considering awareness as main aspect of the ontology. In the following, we outline such ontologies and describe how we integrated them into our ontology.

The *Suggested Upper Merged Ontology* (SUMO)[3] (Niles and Pease 2001) is a free top-level ontology owned by IEEE that was adopted in the IEEE Standard Ontologies for Robotics and Automation (IEEE 2015). SUMO defines general classes across a broad range of domains with the intention to form the basic ontology for various computer information processing systems.

The *Semantic Sensor Network* (SSN) ontology[4,5] (Compton et al. 2012) was proposed by the Semantic Sensor Network Incubator group SSN-XG[6]. SSN is built on top of a lightweight ontology called Sensor, Observation, Sample, and Actuator SOSA (Janowicz et al. 2019). It imports SOSA[7]. It was designed to describe sensor resources and the data they collect in the form of observations. In addition, the procedures used to perform observations, the features of interest and observed properties that are the subject of observation, samples used in the course of observations, as well as actuators can be specified. A more recent version of SSN (newSSN) (Haller et al. 2019) was published lately as a joint standard between W3C and OGC specifying the semantics of sensors, observations, sampling, and actuation.

AWARE is based on the SUMO ontology, and adopts the newSSN concepts to model robotics sensation.

3 AWARE: An Ontology for Situational Awareness

The developed knowledge graph schema AWARE for a proprietary autonomous transport robot in intralogistics incorporates high-level representations of the manufacturing environment and the perceived coexisting assets. Surrounding assets perceived by the robot are modeled as observations. Data streams captured through exteroceptive sensors and intrinsic signals are processed into semantic representations to

[1] https://www.w3.org/
[2] https://www.opengeospatial.org/
[3] http://www.adampease.org/OP/
[4] https://www.w3.org/TR/vocab-ssn/
[5] http://www.w3.org/ns/ssn/
[6] https://www.w3.org/2005/Incubator/ssn/
[7] http://www.w3.org/ns/sosa/

populate the knowledge graph. Further, AWARE models the robots hardware and software components, to associate sensors and signals to the corresponding processing algorithms.

In the following, we first present the development methodology in Sec. 3.1. We then show the adopted ontology design considerations in Sec. 3.2 and the knowledge schema in Sec. 3.3.

3.1 Overall Methodology

We adopted the Ontology Development 101 strategy (Noy and McGuinness 2001) and the ontology editing environment Protégé[8] to develop the ontology presented in this paper. This ontology was designed using OWL 2 DL. Following the above methodology, the development method comprises seven steps:

1. Defining the domain and scope of the ontology, for instance, robotic awareness in automobile manufacturing plant.
2. Considering the re-usage of existing ontologies: the Suggested Upper Merged Ontology SUMO and the Semantic Sensor Network SSN ontologies are extended and adopted in AWARE.
3. Enumerating the important terms in the ontology. For this purpose, we carried onsite inspections to derive the ontology concepts and relations.
4. Defining the classes and their hierarchy: The AWARE ontology includes 91 classes.
5. Specifying the properties of each class, also referred to as slots.
6. Designating the facets of the slots, including slot cardinality, slot-value type and domain, and slot range.
7. Populating the ontology with instances of classes.

3.2 AWARE Design Criteria

The following design criteria have been taken into account in the development:

- *Availability*. AWARE ontology is made public under a persistent URL[9], available under the open CC-BY 4.0 license.
- *Interoperability*. The ontology is grounded in an upper ontology (SUMO) to make its integration with other ontologies easy.
- *Sustainability*. The ontology is integrated in a framework for robot awareness and policy adaptation (El Asmar et al. 2020). The robot awareness framework is deployed in a productive use case in automotive manufacturing plant.

3.3 Ontology Design

AWARE is inspired by analogous robotics ontologies (Suh, Lim et al. 2007; Lim, Suh, and Suh 2010; Lemaignan et al. 2010; Diab et al. 2019; Beetz et al. 2018). Standardized

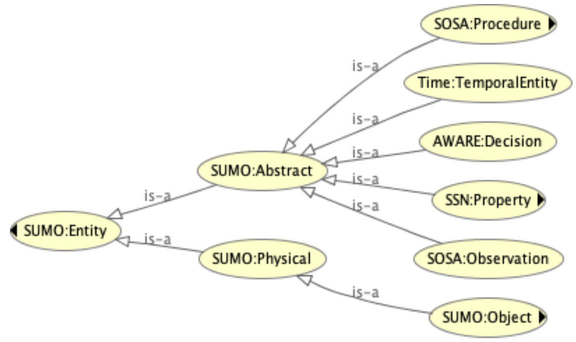

Figure 1: Meta-ontology layer: Taxonomy of the main concepts of AWARE and their relation with SUMO

ontologies (Niles and Pease 2001; Janowicz et al. 2019) have been used or extended whenever possible to ensure extensibility and conformity, and the ontology is designed conformly to the IEEE 1872 terminology (IEEE 2015), W3C, and OGC standards. Furthermore, new introduced classes align with the communication interface published by VDA5050[10].

AWARE is divided similarly to (Suh, Lim et al. 2007; Lim, Suh, and Suh 2010) into the following three layers:

1. A meta-ontology layer representing generic information and serving to align the fundamental objects with the modeling strategy used in SUMO. The highest level classes of SUMO are adopted (*SUMO:Entity*, *SUMO:Abstract*, and *SUMO:Physical*). As shown in figure 1, *SUMO:Object* falls under *SUMO:Physical*. Abstract entities include different properties, observations, procedures and decisions described in section 3.3, as well as temporal entities.
2. The ontology schema layer representing domain knowledge derived from the upper layer. This layer comprises the main elements of the ontology described further in this section: the **environment model**, the **robot perceptions**, and the **decisions** the robot is allowed to make.
3. The instance layer forming the knowledge graph when real data is added as instances of the classes defined in the ontology schema layer, as described in section 4.

In the following, we outline the core components of our ontology, namely the *environment modeling*, the *robot perception modeling*, and the *decision making modeling*.

Environment modeling The shop floor where autonomous transport robots operate is a dynamic environment. Humans, autonomous robots, and manned vehicles cooperate side by side to facilitate material flows. In AWARE, all dynamic assets in the manufacturing plant are incorporated within class *SUMO:Object*. Among *SUMO:Object* there is *AWARE:Person* to represent human agents and *SUMO:Artifact* to represent objects that

[8]https://protege.stanford.edu/

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

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

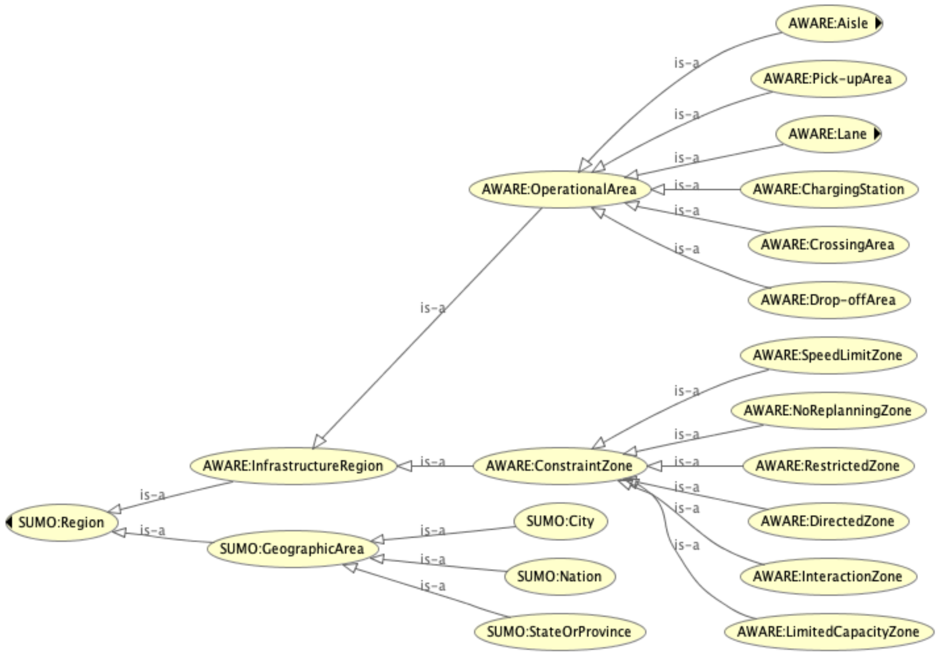

Figure 2: Taxonomy of $Region$

are products of a making including agents present in the plant that are not humans, sensors as well as the plant itself. *SUMO:Artifact* (ref. figure 3) is further ramified into the subclasses *AWARE:Vehicle*, *AWARE:StorageUnit*, and *AWARE:TransportationUnit*. *AWARE:Vehicle* class covers *Aware:MannedVehicles* which are moving objects that are operated by humans such as *AWARE:Forklift*, or autonomous machines such as *AWARE:AGV*. Beneath *AWARE:TransportationUnit* corresponding transportation units are listed, either pulled by another vehicle such as a *AWARE:Trailer isPulledBy AWARE:Tugger*, or lifted by another vehicle such as a *Aware:Dolly isLiftedBy Aware:Forklift*. Further, *SUMO:Region* (ref. figure 2) concept is reused for delimited topographic areas. *SUMO:Region* is partitioned into *SUMO:GeographicArea* and *AWARE:InfrastructureRegion*. *SUMO:GeographicArea* is particularly relevant since general policies and safety rules may differ from one geographic area to another according to the state or country in question. *AWARE:InfrastructureRegion* groups different operations areas listed under *AWARE:OperationalArea* class and constraint zones where different restrictions apply listed under the class *AWARE:ConstraintZone*. The descriptions of different constraint zones are elicited under table 2.

Perception modeling AWARE bridges the gap between low-level data streams coming from robots' sensors suite, and high-level concepts used by humans. For examples raw images data frames are processed into a semantic representation of surrounding industrial assets such as forklifts, pedestrians, driveway. In the following, we describe the classes in the AWARE ontology related to perception of the autonomous robot.

Sensor suite. Sensors are devices that produce signals in one or in multiple dimensions when they are stimulated with phenomena happening in the environment. The class *SOSA:Sensor* incorporates wide range of sensors the robot uses. This is asserted using the *SOSA:hosts* relationship. *AWARE:ProprioceptiveSensor* is used for proprioceptive sensing i.e. measuring values internal to the system such as a *AWARE:BatterySensor* reports its voltage, health state or charge level, while *AWARE:ExteroceptiveSensor* refers to exteroceptive sensing i.e. acquiring information from the robot's environment such as a *AWARE:Lidar* measures distances to objects surrounding the robot. The classes *SUMO:TransitwayObstacle* and *AWARE:ObjectOfFocus* are used to identify objects that are of particular relevance in the LiDAR's and camera's field of focus respectively. In particular, *SUMO:TransitwayObstacle* is used for objects that can act as obstacles to motion along a transitway.

Procedure. The class *SOSA:Procedure* stands for computational models the robot uses to process data of corresponding sensors (*SOSA:Sensor*). This is asserted using the relationship *SSN:implements*. Many sensors' data types can be used in raw format, such as *AWARE:BatterySensor* data since it is provided as a single float value. However, multidimensional data is usually processed to extract key features using suitable algorithms (a *Procedure*). For instance, vision models such as object detection algorithms may be applied to obtain high-level features from raw pixels data. Processing results are abstracted in concepts grounded in the ontology. These high-level semantic concepts are relevant to real-world observations in a manufacturing plant.

Property. Information attributes related to perception capability of an autonomous transport robot are grouped

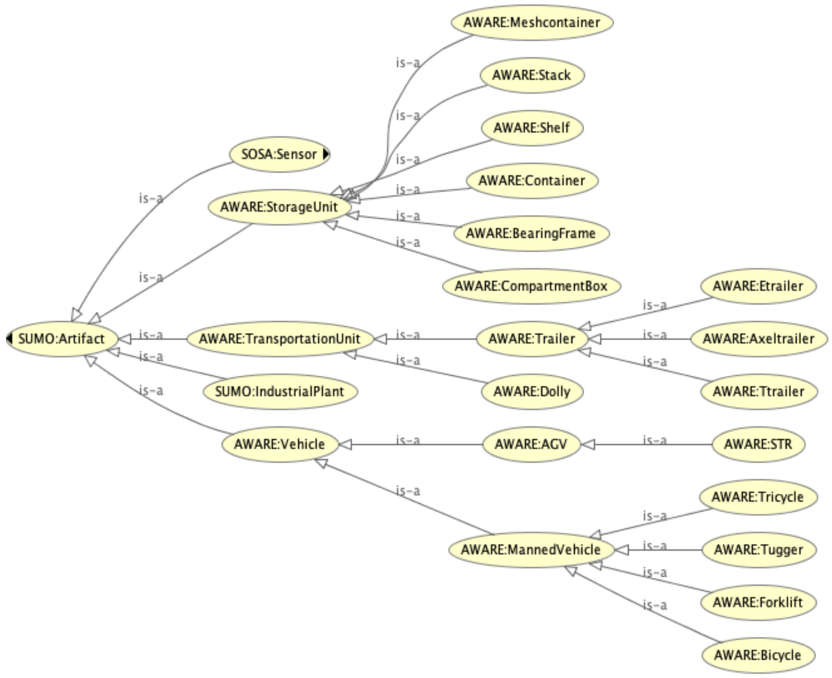

Figure 3: Taxonomy of *SUMO:Artifact*

within the *AWARE:Property* class (ref. figure 4). According to SSN, a property is defined as a quality of an entity, that is an aspect of an entity that is intrinsic to and cannot exist without the entity. This includes visual features namely *AWARE:BoundingBox* to represent the bounding box of an object detected by object detection algorithms, or other attributes such as *AWARE:AGVposition* that indicate the coordinates of the robot, or *AWARE:BatteryInformation* including all the battery information such as *batteryCharge*, *batteryHealth* or *batteryVoltage*. *AWARE:BatteryInformation* data properties among other attributes and their data properties in the ontology were adopted from the communication interface of VDA5050 (see table 1).

Observation. The class *SOSA:Observation* is used to link all the elements of the perception pipeline i.e. *SOSA:Sensor*, *SOSA:Procedure*, *SUMO:Artifact*, *SSN:Property*, and *Time:TemporalEntity*. Through reification, such n-ary relations are expressed to associate the various assets perceived by the sensors across different timestamps. An instance of *SOSA:Observation* is created for every perception, where *SOSA:Observation* is linked to the *SOSA:Sensor* that made the observation, via the relationship defined within SSN *SOSA:madeBySensor*. We incorporate further relevant relationships of *SOSA:Observation* as shown in table 3. Further, the timestamp at which the observation was made is recorded using the relationship *AWARE:hasTimeStamp*. The *Time:TemporalEntity* instance is then linked to its actual *xsd:dateTime* using the relationship *AWARE:hasValue*

Decision Making Modeling Robotic awareness can be grasped with the robot's understanding of its environment. This can be witnessed with the decisions the robot makes according to the state it is in and the dynamics of its environment. In our ontology, the class *AWARE:Decision*, a subclass of *SUMO:Abstract* includes instances of the possible decisions that can be outputted by the situational awareness framework such as *stop*, *increaseSafetyRange* or *decreaseSpeed*.

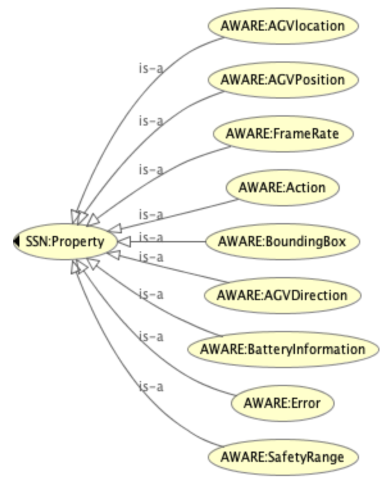

Figure 4: Taxonomy of *Property*

4 Application

In the following, we outline how we applied our ontology in the context of manufacturing. An individual *ego* autonomous vehicle is an instance of *AWARE:STR*. Every *ego* has (1)

Table 1: List of the attributes adopted from VDA5050

Property	VDA description
agvPosition	Defines the position on a map in world coordinates.
actionName	Name of action.
actionID	Unique action identification consisting of the actionName and a postfix starting with "_".
actionDescription	Additional information on the current action.
errorType	Type / name of error.
errorDescription	Error description.
x	X-position on the map in reference to the world coordinate system.
y	Y-position on the map in reference to the world coordinate system.
theta	Orientation of the AGV.
batteryVoltage	Battery voltage.
batteryHealth	State of health of the battery.
batteryCharge	State of charge of the battery.

Table 2: List of distinct zones of operation

Property	Description
$RestrictedZone$	A zone described by a polygon that the vehicle is not allowed to enter.
$DirectedZone$	A directed zone sets directional costs for path planning within the zones.
$SpeedLimitZone$	A zone within which the speed limit is defined.
$NoReplanningZone$	A zone where the vehicle is not allowed to replan its path.
$LimitedCapacityZone$	A zone where only a limited number of vehicles can be present.
$InteractionZone$	A zone that can be accessed after an external state is checked.

its properties such as *serialNumber*, (2) its sensors, and (3) the algorithms/computational models processing the different raw data types. Each sensor is asserted to be *isHostedBy ego* and each algorithm is asserted to be *implementedBy ego*. The area where the vehicle is deployed is defined by classes such as *AWARE:ManufacturingPlant* or *SUMO:City*. The *AWARE:ConstraintZones* and *AWARE:OperationalAreas* are also instantiated according to the plant's map. While operating the classes *AWARE:Action*, *AWARE:Error*, *AWARE:AGVdirection*, *AGVposition*, *AWARE:AGVlocation*, *AWARE:BatteryInformation*, get updated based on information streaming from the master controller and the proprioceptive sensors. As the robot navigates, more insights are obtained and perceptions are inserted in the form of instances of *SOSA:Observation*. The insights are narrowed down to the area of focus of the robot. The area of focus varies with every sensor: for camera input for example, detected objects

Table 3: List of relationships with *SOSA:Observation* being their domain (Subject) or range (object).

Subject	Predicate	Object
SOSA:Observation	*SOSA:madeBySensor*	*SOSA:Sensor*
SOSA:Sensor	*SOSA:madeObservation*	*SOSA:Observation*
SOSA:Observation	*SOSA:usedProcedure*	*SOSA:Procedure*
SOSA:Observation	*SOSA:observedProperty*	observed property
SOSA:Observation	*SOSA:hasFeatureOfInterest*	feature of interest
feature of interest	*SOSA:isFeatureOfInterestOf*	*SOSA:Observation*

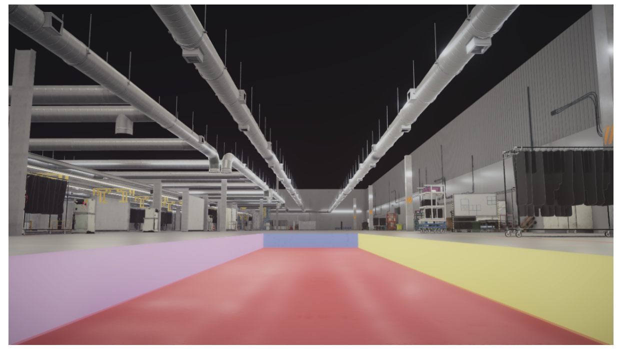

Figure 5: Areas of focus of the robot in camera display (front in red, right in yellow, left in mauve, and opposite in blue)

are filtered out using tuned areas of focus as shown in figure 5. The area of focus of the camera is composed of four adjacent quadrilaterals for filtering out important insights as well as classifying entities observed in front of the robot, on its right, on its left or on the opposite side to it respectively as

- *AWARE:ObjectOfFocusInFront*,
- *AWARE:ObjectOfFocusOnTheRight*,
- *AWARE:ObjectOfFocusOnTheLeft*,
- *AWARE:ObjectOfFocusOnTheOpposite*.

Each observation is characterized with the timestamp at which it was created. Thus, multiple observations can be characterized with the same timestamp. The AWARE reasoner (El Asmar et al. 2020) inspects the data available in the knowledge base and checks it over the behavioral rules in order to infer the best course of action following the prevailing situation. An *AWARE:Decision* is therefore assigned to its corresponding timestamp.

5 Evaluation

To evaluate the AWARE ontology, we performed ontology Verification & Validation (V&V) following the SABiO guidelines (de Almeida Falbo 2014). To this end, human expert judgments were used as follows: Referring to a set of competency questions (CQs) (Brank, Grobelnik, and Mladenic 2005), a human expert analyses whether the developed concepts, relations, and axioms are able to answer all CQs (a selection of competency questions is listed in table 4). We collected competency questions by analyzing the behavior of autonomous transport robots deployed

Table 4: Examples of Competency Questions (CQs). STR refers to the proprietary SMART TRANSPORT ROBOT

Competency Question	Requirement satisfied?
Which sensors retrieve data about the external environment of the robot?	Yes
Which sensors retrieve data about the internal information about the robot?	Yes
Which algorithms can the robot implement?	Yes
What is the level of battery charge?	Yes
How many features of interest can one observation have?	Yes
How many properties can one observation have?	Yes
How many sensors can contribute to making one observation?	Yes
Is ego STR loaded?	Yes
What is the serial number of Ego STR?	Yes
Which type of vehicle is an STR?	Yes
What is the most recent decision?	Yes
Which are manned vehicles?	Yes
Which guidance can the robot provide?	Yes
Which properties can be observed?	Yes
What are the different constraint zones with different regulations in the plant?	Yes
What are the different operational areas in the plant?	Yes
In which plant is the ego STR located?	Yes
In which operational area in the plant is the ego STR located?	Yes
In which constraint zone in the plant is the ego STR located?	Yes
When was observation_1 made?	Yes
Which sensor made observation_1?	Yes
What is the serial number of the sensor that made observation_1?	Yes
Is the observed object an object of focus in front of ego STR?	Yes
Is the observed object an object of focus on the right of ego STR?	Yes
Is the observed object an object of focus on the left of ego STR?	Yes
Is the observed object an object of focus on the opposite side to ego STR?	Yes
What did ego STR observe at timestamp_1?	Yes
Was an observed object also a transitway obstacle?	Yes
Which decision did the STR make at timestamp_1?	Yes

in productive 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. Through AWARE grounding, a transport robot is required to answer questions such as whether there are humans, human-operated vehicles, autonomous vehicles detected in proximity, or whether another transport robot is detected at a charging station area. Furthermore, human expert evaluation, when conducted iteratively during the ontology development process does not only allow to identify missing terms in the ontology, but also to spot irrelevant terms as well. Thus, such evaluation was frequently performed in parallel with the ontology development, which significantly helped in improving the ontology. The final version of the ontology was validated against all CQs, ensuring all questions are answered.

6 Conclusion and Future Work

In this paper we introduced AWARE, an ontology that builds up a comprehensive knowledge representation tailored to the perception of the ego autonomous transport vehicle operating in automobile production intralogistics. Inspired by previous research on robots' cognition tailored to household environment tasks, AWARE builds upon preceding knowledge models in the domain of manufacturing and Internet of Things to advance robot cognition within manufacturing environments. AWARE models the intrinsic and extrinsic perceptions, framing low-level multi-dimensional data streams captured by the robot's sensors into high-level semantic representations. AWARE satisfies interoperability, extensibility, and conformity to established standards, and is consistent with the VDA5050 communication interface published by the German Association of the Automotive Industry.

Our future work will have three main directions: (1) extending the ontology to support projection of future states of the environment given the prevailing state, (2) adapting the behavioral rules specific to automotive manufacturing plants based on established commonsense navigation constraints, and (3) grounding autonomous transport robots intralogistics operations by teaching robots to identify situations that require a change in policy and act accordingly to abide to the operational constraints in order.

References

Beetz, M.; Beßler, D.; Haidu, A.; Pomarlan, M.; Bozcuoglu, A. K.; and Bartels, G. 2018. Know Rob 2.0 – A 2nd Generation Knowledge Processing Framework for Cognition-Enabled Robotic Agents. In *Proc. of the Int. Conference on Robotics and Automation*, ICRA'18, 512–519.

Brank, J.; Grobelnik, M.; and Mladenic, D. 2005. A survey of ontology evaluation techniques. In *Proceedings of the Conference on Data Mining and Data Warehouses (SiKDD 2005)*, 166–170. Citeseer Ljubljana, Slovenia.

Buechel, M.; Hinz, G.; Ruehl, F.; Schroth, H.; Gyoeri, C.; and Knoll, A. 2017. Ontology-based traffic scene modeling, traffic regulations dependent situational awareness and decision-making for automated vehicles. In *2017 IEEE Intelligent Vehicles Symposium (IV)*, 1471–1476. IEEE.

Compton, M.; Barnaghi, P.; Bermudez, L.; et al. 2012. The SSN ontology of the W3C semantic sensor network incubator group. *Journal of Web Semantics* 17: 25–32.

Dahn, N.; Fuchs, S.; and Gross, H.-M. 2018. Situation Awareness for Autonomous Agents. In *2018 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 666–671. IEEE.

de Almeida Falbo, R. 2014. SABiO: Systematic Approach for Building Ontologies. In *Proceedings of the 1st Joint Workshop on Ontologies in Conceptual Modeling and Information Systems Engineering*, ODISE@FOIS 2014.

Diab, M.; Akbari, A.; Ud Din, M.; and Rosell, J. 2019. PMK—A Knowledge Processing Framework for Autonomous Robotics Perception and Manipulation. *Sensors* 19(5): 1166.

El Asmar, B.; Chelly, S.; Azzi, N.; Nassif, L.; El Asmar, J.; and Färber, M. 2020. AWARE: A Situational Awareness Framework for Facilitating Adaptive Behavior of Autonomous Vehicles in Manufacturing. In *Proc. of the 19th Internat. Semantic Web Conference*, ISWC'20, 651–666.

Endsley, M. R. 1995. Toward a Theory of Situation Awareness in Dynamic Systems. *Human factors* 37(1): 32–64.

Fernandez, S.; Hadfi, R.; Ito, T.; Marsa-Maestre, I.; and Velasco, J. R. 2016. Ontology-based architecture for intelligent transportation systems using a traffic sensor network. *Sensors* 16(8): 1287.

Freedman, S. T.; and Adams, J. A. 2009. Improving robot situational awareness through commonsense: Side-stepping incompleteness and unsoundness. *Tech. Rep.* .

Färber, M.; Svetashova, Y.; and Harth, A. 2021. Theories of Meaning for the Internet of Things. In Bechberger, L.; Kühnberger, K.-U.; and Liu, M., eds., *Concepts in Action - Representation, Learning and Application*. Springer.

Geng, X.; Liang, H.; Yu, B.; Zhao, P.; He, L.; and Huang, R. 2017. A scenario-adaptive driving behavior prediction approach to urban autonomous driving. *Applied Sciences* 7(4): 426.

Haller, A.; Janowicz, K.; Cox, S. J.; et al. 2019. The modular SSN ontology: A joint W3C and OGC standard specifying the semantics of sensors, observations, sampling, and actuation. *Semantic Web* 10(1): 9–32.

Harnad, S. 1999. The Symbol Grounding Problem. *CoRR* cs.AI/9906002. URL https://arxiv.org/abs/cs/9906002.

Huang, L.; Liang, H.; Yu, B.; Li, B.; and Zhu, H. 2019. Ontology-Based Driving Scene Modeling, Situation Assessment and Decision Making for Autonomous Vehicles. In *2019 4th Asia-Pacific Conference on Intelligent Robot Systems (ACIRS)*, 57–62. IEEE.

IEEE. 2015. IEEE Standard Ontologies for Robotics and Automation. *IEEE Std 1872-2015* 1–60. doi:10.1109/IEEESTD.2015.7084073.

Janowicz, K.; Haller, A.; Cox, S. J.; Le Phuoc, D.; and Lefrançois, M. 2019. SOSA: A lightweight ontology for sensors, observations, samples, and actuators. *Journal of Web Semantics* 56: 1–10.

Komma, V.; Jain, P.; and Mehta, N. 2012. Ontology development and agent communication in agent-based simulation of AGVS. *International journal of simulation modelling* 11(4): 173–184.

Lasi, H.; Fettke, P.; Kemper, H.-G.; Feld, T.; and Hoffmann, M. 2014. Industry 4.0. *Business & information systems engineering* 6(4): 239–242.

Lemaignan, S.; Ros, R.; Mösenlechner, L.; Alami, R.; and Beetz, M. 2010. ORO, a knowledge management platform for cognitive architectures in robotics. In *Proc. of the Int. Conference on Intelligent Robots and Systems*, 3548–3553.

Lim, G. H.; Suh, I. H.; and Suh, H. 2010. Ontology-based unified robot knowledge for service robots in indoor environments. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 41(3): 492–509.

Morignot, P.; and Nashashibi, F. 2012. An ontology-based approach to relax traffic regulation for autonomous vehicle assistance. *arXiv preprint arXiv:1212.0768* .

Niles, I.; and Pease, A. 2001. Towards a standard upper ontology. In *Proceedings of the 2nd International Conference on Formal Ontology in Information Systems*, FOIS'01, 2–9.

Noy, N. F.; and McGuinness, D. L. 2001. Ontology development 101: A guide to creating your first ontology. URL https://protege.stanford.edu/publications/ontology_development/ontology101.pdf.

Suh, I. H.; Lim, G. H.; et al. 2007. Ontology-based multi-layered robot knowledge framework (OMRKF) for robot intelligence. In *Proc. of the Int. Conference on Intelligent Robots and Systems*, 429–436.

Tandon, N. 2016. *Commonsense Knowledge Acquisition and Applications*. Ph.D. thesis.

Wolf, P.; Ropertz, T.; Feldmann, P.; and Berns, K. 2019. Combining Onthologies and Behavior-based Control for Aware Navigation in Challenging Off-road Environments. In *Proceedings of the 16th Int. Conference on Informatics in Control, Automation and Robotics*, ICINCO'19, 135–146.

Xiong, Z.; Dixit, V. V.; and Waller, S. T. 2016. The development of an Ontology for driving Context Modelling and reasoning. In *Proceedings of the 19th International Conference on Intelligent Transportation Systems*, ITSC'16, 13–18.

Zhao, L.; Ichise, R.; Liu, Z.; Mita, S.; and Sasaki, Y. 2017. Ontology-based driving decision making: A feasibility study at uncontrolled intersections. *IEICE TRANSACTIONS on Information and Systems* 100(7): 1425–1439.