An Extensible Semantic Data Fusion Framework for Autonomous Vehicles

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***Abstract*—Fully autonomous vehicles may still be an elusive goal, however, research in the deployment of relevant Artificial Intelligence technologies in the domain is rapidly gaining traction. A key challenge lies in the fusion of all the diverse information from the various sensors on the vehicle and its environment. In this context, ontologies and semantic technologies can effectively address this challenge by semantically fusing heterogeneous pieces of information into a uniform Knowledge Graph. This paper presents CASPAR, an extensible semantic data fusion platform for autonomous vehicles. Two use case scenarios are also presented that demonstrate the framework's versatility.**

Keywords-Autonomous vehicles; ontologies; knowledge graphs; semantic data fusion; AI.

I. INTRODUCTION

Although fully autonomous vehicles are still an elusive goal, research in the field is rapidly gaining traction, with relevant studies estimating the value of the automotive AI market at a little over $10.5 billion by 2025 [1]. Consequently, most major automotive manufacturers are increasingly investing in the field.

The key challenge in this domain lies in the fact that AI systems operating in such dynamic settings must deal effectively with large volumes of streaming data generated by the various sensors on the vehicle (e.g., camera, radar, Light Detection and Ranging – LiDAR, Global Positioning System – GPS, etc.) as well as by the vehicle's environment (e.g., pervasive inputs, weather data, other vehicles, etc.). The fusion of all this diverse information is, thus, a non-trivial and highly error-prone process.

In this context, semantic technologies and, most prominently, ontologies seem like a natural fit for semantically fusing heterogeneous pieces of information into a uniform knowledge representation model, i.e., a Knowledge Graph (KG). This paper presents ongoing work on an extensible semantic data fusion framework for autonomous vehicles, called CASPAR [2]. The framework is part of a larger platform being developed within the context of the CPSoSaware EU-funded project [3].

The rest of the paper is structured as follows: Section 2 gives an overview of related work on deploying semantic technologies in the domain of autonomous and connected vehicles. Section 3 presents the proposed approach, describing the architecture, input sources, as well as the semantic data fusion component. Section 4 presents two use case scenarios and their evaluation, and, finally, Section 5 concludes the paper with some final remarks and directions for future work.

II. RELATED WORK

It was roughly 20 years ago that the issue of data heterogeneity in the automotive industry was gradually emerging as a critical challenge, and the first approaches proposed the addition of a semantic layer on top of the lower-level sensors and systems of the vehicle. In collaboration with the German car manufacturer Audi AG, the authors in [4] proposed an ontology for representing the various parts and sensors of a car. Other early approaches adopted ontology-based representation of the context and the situations surrounding the vehicle, like, e.g., the road network and all detected objects in the scene, an estimation of the behaviours of other traffic participants, as well as the mission goal of the own vehicle [5].

In the same context, the works presented in [6]-[8] propose ontology-based representations of road intersections and road infrastructures that could serve the basis for traffic models and systems that could predict conflicts between vehicles reaching the same intersection.

Extending the scope beyond representing vehicle- and sensor-related aspects, other approaches adopt a user-centred view of the world, also considering aspects like the mental and physiological state of the driver [9][10] or their grip force and alcohol density [11].

In more recent works, bigger players entered the game, and more holistic Advanced Driver Assistance Systems

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(ADAS) were proposed, utilizing a wider range of (the now more mature) semantic technologies. [12] and [13] present intelligent decision-making systems, as part of an ADAS, for assisting autonomous vehicles in making appropriate decisions during certain cases. The systems consist of an ontology-based KG, as well as a set of Semantic Web Rule Language (SWRL) rules for representing traffic regulations and spatiotemporal relationships between entities. In both works, thorough evaluations regarding semantic reasoning and result-set retrieval times are conducted, but, arguably, the respective sizes of the KGs are rather small.

The authors in [14] present a more standards-oriented approach, proposing the Vehicle Signal and Attribute Ontology (VSSo) that is based on the Sensor, Observation, Sample, and Actuator (SOSA) ontology [15] for representing sensor measurements, on the Vehicle Signal Specification (VSS) [16] for representing domain-pertinent aspects (i.e., vehicle signals), and on the Web of Things principles [17] for defining technology and protocol-independent interactions with Web Things. This combination facilitates the decorrelation from automotive standards, enabling the collection and analysis of sensor data coming from vehicles of different models and brands, and allows integrating car data with data coming from other Internet-of-Things (IoT) sources from the Web. As suggested by the authors, VSSo can form the basis for various applications like car fleet monitoring, car trajectory mining, contextual representation of a car and interaction between any car and web services.

Compared to the existing approaches presented above, our framework does not ingest raw sensor measurements into the KG, but instead adds the higher-level outputs generated by analyses performed by other components at a lower level, like, e.g., Driver Monitoring Systems (DMSs), driver's wearables, and visual odometers. This approach offers richer insights about various aspects of the vehicle and the driver, like, e.g., the system health or the driver's state during a driving session.

III. Proposed Approach

This section presents our proposed approach, focusing on the architecture, input sources, as well as the CASPAR semantic data fusion component.

A. Architecture

An overview of the system encompassing the semantic data fusion framework is presented in Figure 1. Adopting the microservice methodology [18], we defined a set of independent, replicable services that collaboratively fulfil the system's functionality. For the communications among services, we deployed RabbitMQ [19], a popular open-source message broker that is scalable and industry-ready.

The system components in the monitoring layer periodically collect and analyze data related to the driver, the vehicle and its surroundings. Five monitoring components (DSO, LeGO, CL, DMS and OFE) - all introduced in the next subsection - are currently integrated. However, the modularity provided by the microservice approach, coupled with the straightforward system design, enables the integration of third-party data sources (e.g., weather or traffic condition reports) with minimum effort.

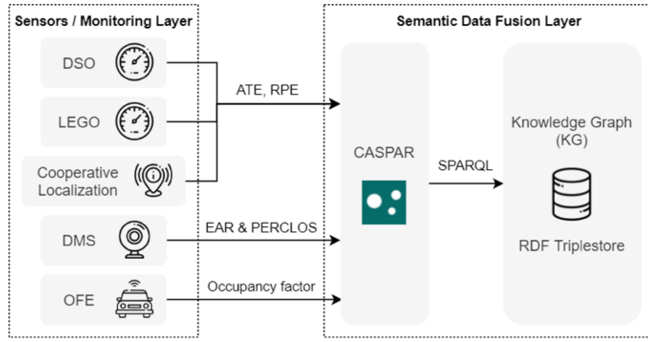

Figure 1. Overview of the system architecture.

The outputs and observations produced by the monitoring layer are communicated to the semantic data fusion layer via a dedicated RabbitMQ exchange. At this stage, they are mapped to ontology concepts, resulting in a unified Knowledge Graph (KG), which is instantiated in a Resource Description Framework (RDF) triplestore by the CASPAR component, which is further described in a next subsection.

B. Input Sources

1) Odometry Algorithms: The quantitative trajectory evaluation of odometry algorithms is an issue which has been examined thoroughly by the research community. A few metrics have been proposed over the last years, of which the *Absolute Trajectory Error* (*ATE*) and the *Relative Pose Error* (*RPE*) are the most popular. More specifically, let us assume that the output of a Simultaneous Localization and Mapping (SLAM) algorithm, thus the estimated trajectory is a set of n distinct poses $P_i \in SE_3$, where SE_3 is the Special Euclidean space of rigid body transformations in three dimensional space. Each element of this space can be expressed in the form of a 4x4 matrix:

$$M = \begin{pmatrix} R & T \\ 0 & 1 \end{pmatrix}$$

where $R \in SO_3$ is the rotation part, $T \in R_3$ is the translation part, and SO_3 is the special orthogonal group that contains the rotations. Accordingly, the ground truth trajectory is consisted of n $G_i \in SE_3$ poses in an arbitrary coordinate system.

In order to compute the ATE, which gives us the total consistency of the algorithm, we have to align the two trajectories using an algorithm like Horn's method [20]. Consequently, the ATE error matrix E_i for each of the n estimated poses, can be computed by the following equation:

$$E_i := G_i^{-1} A P_i$$

where A is the alignment matrix. Usually, we use the Root Mean Square Error (RMSE) of ATE which is calculated as follows [21]:

$$E_{rmse} := \sqrt{\frac{1}{n}\sum_{i=1}^{n}\|T_i\|^2}$$

The RPE is a metric which indicates the accuracy of the algorithm over a specific time step. Let us assume that we have a common time step Δ for both the algorithm and the ground truth trajectory, the RPE matrix R_i^{Δ} can be calculated by the following equation [21]:

$$R_i^{\Delta} := (G_i^{-1}G_{i+\Delta})^{-1}(P_i^{-1}P_{i+\Delta})$$

The RMSE for the translation of RPE is calculated as in the case of ATE.

The odometry algorithms used in this paper are presented below:

Direct Sparse Odometry (*DSO*) [22] is a state-of-the-art monocular visual odometry solution, relying on the Camera sensor. Contrast to most related methods, it features the combination of Sparse+Direct: it optimizes the photometric error defined directly on images, without exploiting any geometric prior, using the so-called keypoints from some keyframes. One of the main benefits of keypoints is their robustness to photometric variations. In addition, the main drawback of adding geometry priors is the introduction of correlations between geometry parameters, which render a statistically consistent, joint optimization in real time infeasible. DSO provides a strategy for keyframes and keypoints management, which leads to a windowed optimization problem, solved by Gauss-Newton (GN) method. Only the most useful frames out of consecutives frames are kept (tracking). And then, some active points are determined in order to estimate the pose of the vehicle using GN.

LeGO-LOAM [23] is a lightweight and ground-optimized LiDAR odometry solution, which introduces a two-step Levenberg Marquardt (LM) optimization for pose estimation. As shown in Figure 2, before the feature extraction module, the point cloud from LiDAR is being processed by the segmentation module.

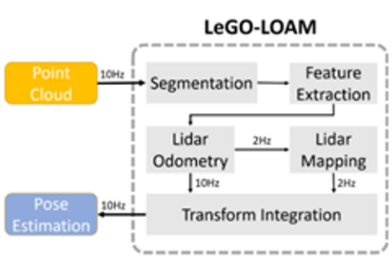

Figure 2. LeGO-LOAM system overview.

The segmentation model is responsible for creating clusters of points from the point cloud. More specifically, it assigns three related values to individual 3D points: (a) label as a ground or segmented point, (b) column and row index in the depth image (created by projecting all points to the image plane), (c) depth value. Feature extraction is responsible for categorizing the points from segmentation to either planar or edge features. And finally, the pose is estimated by performing LM optimization using these two groups of vehicles between consecutive LiDAR scans.

Cooperative Localization (*CL*) is expected to further improve the positioning accuracy of the Localization sub-system of Connected and Autonomous Vehicles. Vehicles, apart from the advanced sensors of LiDAR, Camera, etc., benefit from direct V2V communication and exchange of rich information, for increased perception and scene analysis ability. Graph Laplacian processing [24][25] enables the fusion of heterogeneous measurements from vehicles in a linear and compact way, contributing to efficient location estimation. It makes use of connectivity representation of collaborating vehicles, along with the inter-vehicular measurements (noisy distances, angles, and positions) provided by the Perception sub-system, in order to formulate a linear least-squares estimation problem. Combined with the Extended Kalman Filter, it also exploits the motion properties of vehicles, significantly increasing location accuracy [26]. Note that CL could be useful for mitigating GPS location spoofing cyberattacks [27].

2) Driver Monitoring System (DMS): Our DMS module captures frontal facial images of the driver to assess fatigue levels based on the activity of the eyes. The driver's drowsiness is measured based on two metrics, the *Eye Aspect Ratio* (*EAR*) [28] and the *PERcentage of Eye CLOSure* (*PERCLOS*) [29]. To obtain the facial landmarks we use the Dlib toolkit, which provides us with 68 facial landmarks characterizing various facial features, such as eyes, nose, mouth, etc. From those 68 points, 12 points correspond to the eyes. We use these landmarks to calculate the ratio of the vertical and horizontal lines defined by the eclipse that is fitted to the eye. This ratio is computed as:

$$EAR = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

Typical values indicating eyelid closure were determined at EAR < 0.2 in [28]. In our tests, we found that an EAR threshold closer to 0.25 performs better in this simulation context.

The PERCLOS measure is defined as the percent of the time the eyelid occludes the pupil (EAR < 0.25) within a *K*-second moving window, where *K* can be tuned by the user. Typical values of K are around 60 seconds. Therefore, PERCLOS is calculated as:

$$\text{PERCLOS}(\%) = \frac{\text{num of frames where eyes are closed}}{\text{frame interval length}} \times 100$$

In literature, the values that have been suggested as representative of low drowsiness state are typically under the 0.25% PERCLOS and 70% or 80% (known as PERCLOS70 and PERCLOS80, respectively) for high drowsiness [30].

3) Occupancy Factor Estimation (OFE): The Occupancy Factor (OF) is an empirical metric, extracted by analysing the point cloud of the scene that has been acquired by the LiDAR device. It indicates how "clear and open" the road is beyond

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the driver's field of view. Based on this value, the road's condition can be separated into three categories: (a) Safe road without objects, (b) Road with small obstacles (e.g., potholes) or cars at a far distance from the vehicle, (c) Road with a lot of traffic, parked cars, etc.

OF is estimated via point cloud processing. In more detail, after the acquisition of the point cloud by the LiDAR, a geometry processing technique is applied to estimate the saliency map of the point cloud scene [31].

The saliency map extraction assigns at each vertex of the point cloud a value based on its distinctiveness (geometrical importance). To visualize the saliency map of the point cloud, we quantize the range of value into 64 classes which we map to 64 colours, as presented in Figure 3. The lowest saliency values correspond to deep blue, while the highest values correspond to deep red. Vertices that lie in totally flat areas take the lowest value (as not being salient), while vertices lying in very sharp corners take the highest value.

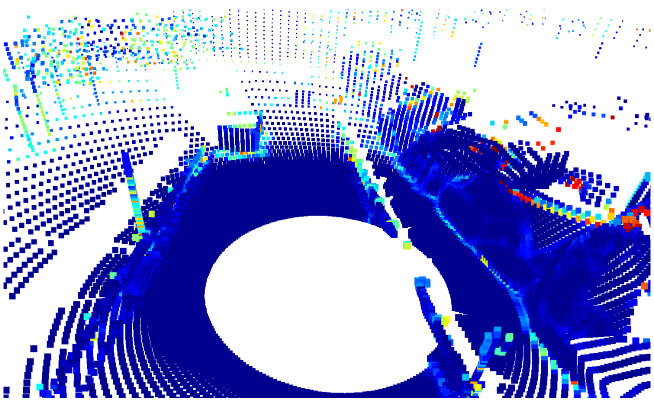

Figure 3. Example point cloud showcasing our color mapping.

The next step addresses the spatial scene analysis. Specifically, we are interested in the segmentation of the road. For estimating OF, we take into consideration only these set of vertices, denoted as *N* below, that: (a) belong to the region of the road and (b) correspond to the lowest saliency value (i.e., totally flat area of the road). Finally, OF is estimated as the sum of the inverse norm2 distance between each vertex, of the previously aforementioned set of vertices, and the point v_1 $(0,0,0)$ that represents the centre of the LiDAR sensor.

$$\mathrm{OF} = \sum_{\forall i \in \mathcal{N}} \frac{1}{||v_i - v_1||_2}$$

The higher the OF value, the less occupied the road for driving.

C. Semantic Data Fusion

The integration of inputs (see previous subsection) to the unified KG is handled by *CASPAR* (*Structured Data Semantic Exploitation Framework*), our domain-agnostic tool for the automated retrieval and fusion of structured data from disparate sources into domain-specific semantic models, facilitating the discovery of new knowledge along with the extraction of actionable insights.

CASPAR is based on the ontology population principles presented in recent works of ours [32][33]. In a nutshell, the tool administers a set of interconnected mechanisms for transforming data into knowledge, represented in a machine-interpretable and exploitable format (RDF). These mechanisms incorporate: (a) the automated acquisition of structured data from user-defined sources (APIs, databases, messaging buses, etc.), (b) the mapping of input data fields to semantic entities (concepts, relationships, etc.), (c) the semantic fusion and population of knowledge into a semantic repository, (d) the semantic enrichment of existing knowledge from external Linked Open Data repositories, and, (e) the application of rule-based semantic reasoning to unveil underlying or generate new knowledge.

For the purposes of this work, the SOSA ontology [15] serves as the core semantic model for describing sensors and their observations, the studied features of interest and the observed properties. As described in the next section, the core model is populated with the outputs generated by the input sources, i.e., other analysis components in the CPSoSaware project architecture.

IV. Scenarios and Results

This section presents two use case scenarios applying the proposed architecture and semantic data fusion component. Evaluation results are also discussed.

A. Scenario #1: Evaluate the Robustness of Odometry Algorithms

In the first scenario we rely on an end-to-end testing framework, based on the CARLA open-source urban driving simulator [34], for generating synthetic sensory data and evaluating the three aforementioned odometry algorithms against different weather and lighting conditions. Each algorithm uses a different modality and our purpose is to study the effect of the changing conditions on the efficiency of each algorithm.


```
{
  "observations" : [
    {
      "timestamp": "2021-01-01T00:38:35.743042",
      "property": "ate_trans",
      "result": 2.4164187908172607,
      "source": "dso"

    },
    {
      "timestamp": "2021-01-01T00:38:35.743042",
      "property": "ate_rot",
      "result": 2.099885940551758,
      "source": "dso"}
    ]
    ...
}
```


Figure 4. Excerpt of the ATE and RPE observations submitted to CASPAR.

Based on the architecture described above, ATE and RPE measurements are sent via the message bus to the CASPAR semantic data fusion framework and are ingested into the KG. Indicatively, 1226 observations were submitted for a driving simulation of 126 seconds. Figure 4 displays an excerpt of the observations, while Figure 5 illustrates the representation of the same sample observations in Graffoo format [35] fused inside the KG. As seen in the latter figure, no conflict resolution considerations are raised, since SOSA facilitates the explicit association of observations to the respective sources via `sosa:madeBySensor`, as well as the representation of different observed properties via `sosa:observedProperty`.

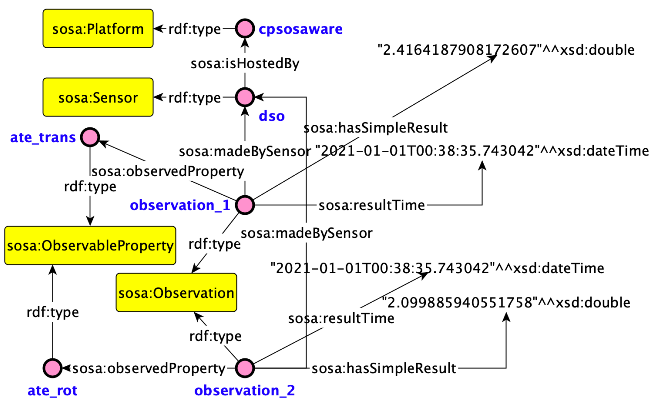

Figure 5. Excerpt of the ATE and RPE observations submitted to CASPAR.

After the population of the KG is complete, useful insights regarding the performance of the algorithm can be extracted. Figure 6 displays such an example, where the LiDAR-based odometry algorithm (LeGO-LOAM) presents better results with regards to RPE and seems to be more robust, constituting thus a better candidate in conditions similar to the specific simulation session.

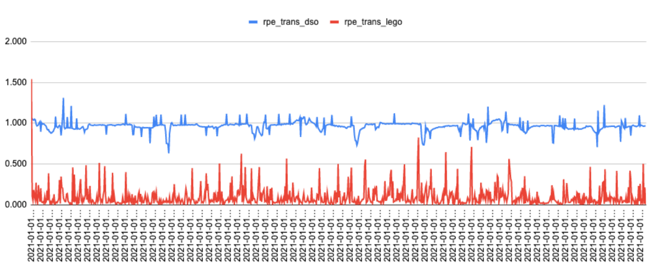

Figure 6. Performance comparison of LeGO vs DSO for a simulation session.

More specifically, as illustrated in Figure 6, the LiDAR odometer outperforms the visual odometer in terms of the relative drift between two consecutive poses, which depicts an indicative use case in which the reduced environmental light (night) resulted in the downgrade of the DSO performance.

Additionally, LIDAR's robustness has been also pointed out in [23]. Specifically, vision-based methods are sensitive to illumination and viewpoint changes. On the contrary, LiDAR functions well even at night and the high resolution of many 3D point-clouds permits the capture of the fine details of an environment at long ranges, over a wide aperture.

However, it must be noted that the superiority of LiDAR has only been identified in a specific set of scenarios. In the future, we plan to extend the set of scenarios and include more use cases (e.g., road bumps, sudden breaks, dynamic objects etc.), in order to further examine the robustness of the algorithms.

B. *Scenario #2: Calculate Risk Levels during a Driving Session*

In the second scenario, our objective is to inform the driver about potential risks during a driving session. We focus on two factors: The driver's drowsiness and the free available space of the road. For this purpose, two components have been developed (see also Figure 1): (a) the Driver Monitoring System (DMS) component, and (b) the Occupancy Factor Estimation (OFE) component.

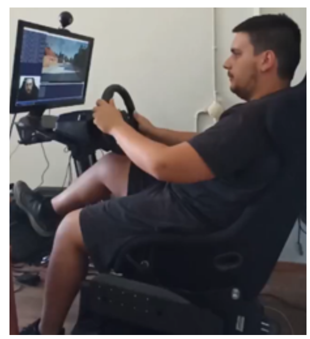

Figure 7. Driving simulation setup for integrating DMS and OEF.

For the evaluation of our implementation, we integrated the DMS with CARLA [34], whose spectacularly photorealistic graphics provide an immersive driving experience. The simulator provides the flexibility to design a variety of driving scenarios under different states of driver's drowsiness and different conditions of the road (e.g., the state of the traffic), in a safe environment for the operator who tests the implementation. The setup of the integration (see Figure 7) uses the Logitech G29 steering wheel for enhancing the driving sense, as well as a static web camera that captures the face of the driver in real-time.

Similar to the previous scenario, the DMS and OFE modules submit their observations, namely the PERCLOS and OF measurements, to CASPAR via RabbitMQ. However, an upgrade compared to scenario #1 entails a set of rules (see Table I) for calculating the risk levels during the simulated driving session. Risk level 1 corresponds to a "low risk" driving situation, where the driver is focused and drives carefully in a full open-eyed state (without any observed drowsiness). Moreover, the road is free from other vehicles, providing thus an unobstructed area for driving. On the other hand, risk level 3 corresponds to a "high risk" driving situation where the driver demonstrates intense drowsiness, as identified by the facial analysis of the DMS component, with intense drowsiness and/or the unobstructed area of the road is

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restricted (due to obstacles, a lot of traffic, small-ranged road, etc).

TABLE I. SET OF RULES FOR CALCULATING THE RISK LEVEL

	PERCLOS < 0.25	*PERCLOS >= 0.25 & <0.7*	*PERCLOS >= 0.7*
OF > 280	Low risk (1)	Be aware (2)	High risk (3)
OF <= 280 & >200	Low risk (1)	Be aware (2)	High risk (3)
OF <= 200	Be aware (2)	High risk (3)	High risk (3)

After the KG is populated through CASPAR, according to the approach described before (see Figure 5), the above ruleset is executed in the form of a respective SPARQL query "on-top" of the KG. The result is a risk level report, as illustrated in Figure 8. Outputs like this can constitute parts of reports, e.g., after traffic accidents.

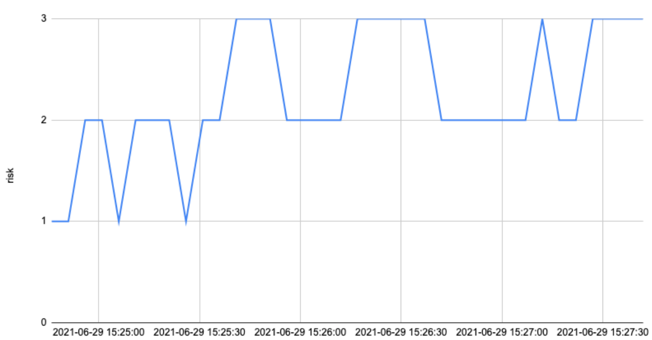

Figure 8. Output graph indicating the risk levels during a driving session.

Observing Table I and Figure 8, we see that when PERCLOS is higher than 0.7 (i.e., intense drowsiness), the risk level is always equal to 3 (i.e., high risk), independently of the value of OF. On the other hand, when PERCLOS is lower than 0.25, then the risk level is 1 (i.e., low risk), and correspondingly when the PERCLOS ranges from 0.25 to 0.7, the risk level is 2 (i.e., be aware). In these cases, the risk level is changed (level up) only when OF is lower than 200 indicating that the driver has to draw extra attention.

V. CONCLUSION

This paper presented CASPAR, a semantic data fusion framework for autonomous vehicle that is part of a larger platform in the context of an EU-funded project. The inputs to CASPAR constitute analysis results generated by other components in the platform and, this way, higher-level and richer insights can be derived regarding various aspects of the vehicle and the driver. In this context, the two scenarios presented in the paper demonstrate the framework's functionality and versatility in the domain.

However, this is largely still a work-in-progress. Thus, our next steps involve testing the semantic data fusion framework in a wider variety of simulation scenarios involving more sources of information (e.g., steering frequency, weather info, biometrics, etc.) and more challenging conditions (e.g., dynamic objects, reduced visibility, sudden braking, etc.). This would also entail extending the rule-base accordingly. A parallel future direction also involves considering the extraction of real-time analytics and insights, which, thus far, was not possible due to challenges in the scalability and performance of the triplestores we considered.

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