Towards Traffic Scene Description:
The Semantic Scene Graph

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Abstract— For the classification of traffic scenes, a description model is necessary that can describe the scene in a uniform way, independent of its domain. A model to describe a traffic scene in a semantic way is described in this paper. The description model allows to describe a traffic scene independently of the road geometry and road topology. Here, the traffic participants are projected onto the road network and represented as nodes in a graph. Depending on the relative location between two traffic participants with respect to the road topology, semantically classified edges are created between the corresponding nodes. For concretization, the edge attributes are extended by relative distances and velocities between both traffic participants with regard to the course of the lane. An important aspect of the description is that it can be converted easily into a machine-readable format. The current description focuses on dynamic objects of a traffic scene and considers traffic participants, such as pedestrians or vehicles.

I. INTRODUCTION

The verification and validation of automated driving functions is an essential part of its homologation process. Recent research suggests that statistical validation of such a system is difficult, if not impossible, to sustain [1]. The large amount of kilometers which is required to be driven in order to classify the driving function as ‘safe’ is not feasible in practice [2]. Scenario-based testing is expected to significantly reduce the effort that would otherwise be required. The question arises, which traffic scenarios and consequently which traffic scenes are of relevance. To tackle this challenge, it must first be made possible to describe traffic scenes. The description model must be able to compare and evaluate a traffic scene from different domains. With conventional description methods, it is difficult to compare scenes with, for example, different road geometries, at different locations or with varying traffic participants in a scalable way. That’s the reason a model must be found that can describe the most diverse traffic scenes in such a way that similar ones can not only be clustered, but also be classified. Furthermore, the entities types and relations types should be reduced to a minimum. Here, a concept of the Semantic Scene Graph model is proposed and utilized. With this model, traffic scenes can be described in relation to the road topology and different scenes can be compared with each other, independent of the location. The relations between traffic participants are described by semantically classified edges. This abstract description facilitates machine readability and makes it practical to apply machine learning methods to traffic scenes. In addition, Semantic Scene Graphs can be analyzed and processed by graph neural networks. In the context of autonomous driving as well as in its validation, it is important to understand a traffic scene. The description plays a role in finding similar scenes for efficient validation of autonomous driving functions. At the same time, a better understanding of other traffic participants could improve the decision-making of a driving function.

An early version of the description model has already been presented in [3]. In this paper, an improved version, in terms of generalizability and applicability, is proposed and the mapping of the scene and the resulting relations are concretely discussed.

While there exist multiple definitions of the terms scene and scenario, this work will follow the definitions of Ulbrich et al. [4], where only dynamic elements (traffic participants) are considered.

This paper is structured as follows: In section II we provide a review of existing traffic scene descriptions and related work. In section III and IV we give a detailed definition of the Semantic Scene Graph and how it is implemented concretely. In section V, properties of the Semantic Scene Graphs and its implementation are evaluated with examples. Finally, in section VI we conclude this contribution.

II. STATE OF THE ART

While there are other concepts [5]–[7], in recent years, a variety of ontologies on the assessment of the environment of an automated driving system have been published. In terms of architecture, an ontology can be divided into terminological boxes and assertion boxes. The terminological boxes contain the general background knowledge, consisting of the concepts, the relations, the attributes, the axioms and rules. The assertion boxes contain instances or specific objects and relations between them [8].

Ulbrich et al. [9] represent a graph-based scene representation similar to the W3C Web Ontology Language (OWL) standard [10]. A hybrid approach is chosen, where metric and topological information of the lanes (lane markings and their topological relations) are combined with a semantic description which links dynamic elements to the corresponding lane segment. Bagschik et al. [8] present a method for knowledge-based scene creation, where the description of the environment is based on the five-layer model of Schulte [11]. Most ontologies in the context of traffic scene description use or are oriented towards the five level model and represent a scene using the Resource Description Framework (RDF) [12] [13]. The focus of the ontologies is limited to the

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spatial composition of the scene. In the context of automated
driving, this spatial composition is about entities’ locations
and their spatial connections to other objects. Huang et al.
[14] and Kohlhaas et al. [15] create a reasoning structure of
eight regions around the vehicle under consideration, which
describe its surrounding and its spatial interaction with other
vehicles in a semantic way. An object can be on the left, right
or in the middle, behind or in front of the vehicle. This model
may be good for describing the traffic scene on a highway,
but as soon as the lanes are not truly parallel and straight,
for example in an urban intersection with complicated lane
topology, this model will not be able to clearly represent the
facts of the relations. Armand et al. [16] describe a framework
which interprets a traffic scene based on the contextual
information between different road entities. The semantic
relations are set to a fixed classification with no possibility
to hold continuous values. Petrich et al. [17] introduce a
tensor-based approach which considers relations between
terms in combination with the environment to model high-
level context information. This approach generalizes over a
variety of scenes (denoted as situations) by using a unified
description. This approach is similar to the model presented
in this paper, but considers exclusively semantic attributes of
the relations. In addition, no specific differentiation is
made between vehicles driving on intersecting lanes and
those driving on parallel, adjacent lanes. For environmental modeling of behavioral prediction, there are
some approaches to model entities of the traffic scene as
nodes and their relations as edges. A majority of them
use fully connected graphs between different entities within
a certain radius [18] [19]. Diehl et al. [20] models traffic
cenes on freeways using a graph and includes nearby and
preceding vehicles in its model. Edges are weighted by the
inverse relative distance between entities. Ma et al. [21]
presents a similar approach, where the feature representation
is generated by a machine learning approach. Here, the edges
are equipped with weight vectors. Furthermore, the edges are
divided into different classes.

As shown in the above excerpt of the state of the art, it can
be seen that the current scene descriptions follow an approach,
which focuses on spatial information and often neglects
interactions between entities. Often, immediate relations
between different entities of a scene are only described
indirectly or not at all. In order to be able to infer the specific
causes, for example, when classifying a scene with the help
of machine learning approaches, it is advisable to keep the
input space as specific as possible. For this reason, all driving
related relations and the resulting relations’ attributes are
explicitly modelled in the proposed scene description.

III. ARCHITECTURE OF THE FRAMEWORK

In this section, the architecture of the proposed framework,
including the creation of the relations in the scene, are
described in detail. Table I provides an overview of all
symbols used in the following chapters.

| Symbol | Description |
|--------|-------------|
| A      | Adjacency matrix |
| B      | Node attribute matrix |
| C      | Edge attribute matrix |
| C_k    | k-th edge attribute vector in C |
| d_C    | Tangential distance in Frenet space |
| d_p    | Tangential distance to intersecting point in Frenet space |
| d_n    | Normal distance to intersecting point in Frenet space |
| δ      | One-hot-encoding function |
| ε_{scene} | Edge in G_{scene} |
| ε_{road} | Edge between node a and b in G_{road} |
| E_{road} | Set of all edges in G_{road} |
| E_{scene} | Set of all edges in G_{scene} |
| G_{road} | Road graph |
| G_{scene} | Semantic Scene Graph |
| I      | Set of all traffic participants in the scene |
| I’     | Set of filtered traffic participants in the scene |
| κ_{rel} | Classification of an edge in G_{scene} |
| κ_{obj} | Classification attribute of a node |
| l_i    | Length and width of traffic participant i |
| m_i    | Projection identity of traffic participant i on segment a |
| p_{ab} | Path between two nodes (a, b) in G_{road} |
| p_p    | Length of path p |
| P_i    | Probability of m_i |
| Φ      | Angular deviation compared to the lane |
| ψ      | Yaw of traffic participant i |
| S_{gt}(t) | Scene state to a given time t |
| σ_d, σ_p | Standard deviations of the Gaussian of P(m_i) |
| t      | Timestamp / time |
| u      | Node attribute vector |
| v_{road} | Node u in G_{road} |
| v_{scene} | Node u in G_{scene} |
| V_{road} | Set of all nodes in G_{road} |
| V_{scene} | Set of all nodes in G_{scene} |
| x_i, y_i | x, y-position of traffic participant i |
| x̅, y̅ | Velocity in x, y-direction of traffic participant i |
| x̅̅, y̅̅ | Acceleration in x, y-direction of traffic participant i |
| X_i    | State of traffic participant i |
| X̅_i    | Set of projection identities of traffic participant i |

TABLE I: Symbols

A. Input Object Data

As a basis for the analysis of traffic scenes, corresponding
data is necessary. The prerequisite for the data to be processed
by the Semantic Scene Graph framework is that for each
desired point in time, all traffic participants I can be assigned
to a discrete state. The state X of the traffic participant i
(i ∈ I) is defined as follows:

\[ X_i = \{x_i, y_i, \psi_i, x̅_i, y̅_i, x̅̅_i, y̅̅_i, w_i, l_i, κ_{obj}^i\} \] (1)

The traffic participants are considered exclusively in a planar
\( \mathbb{R}^2 \) coordinate system. Here, \( x_i \) and \( y_i \) describe the geometric
center of the traffic participant in a local metric coordinate
system, whose origin is usually defined by a geodetic
reference point. \( \psi_i \) specifies the orientation (yaw angle) of
the vehicle. \( x̅_i, y̅_i \) and \( x̅̅_i, y̅̅_i \) specify the traffic participant’s
two-dimensional velocity and acceleration, respectively of the
traffic participant, in the direction of the respective axis. The
size of the respective object box is described by the width \( w_i \)
and the length \( l_i \). In addition to the geometric information, an
object is described by its classification \( κ_{obj}^i \) (Car, Pedestrian,
Truck, ...).
The states $\mathcal{X}$ of all traffic participants of a specific time step are then combined to a scene and described by the scene state $S_{\text{rgz}}(t)$:

$$S_{\text{rgz}}(t) = \{ \mathcal{X}^i(t) | i \in I \}. \quad (2)$$

Every dataset, which allows for the calculation of the above described states $\mathcal{X}$, can be chosen as input data format. Examples are the TAF dataset [3], inD dataset [22] or the INTERACTION dataset [23].

### B. Road Data and Additional Information

In addition to the object lists, highly accurate road maps are required as input data. It is particularly important that the road topology, i.e. information about which lanes are connected to each other and how, is included.

The road map is described by a directed graph $G_{\text{road}}$ defined by $(V_{\text{road}}, E_{\text{road}})$. Each elementary road segment (lane) is described by a node $v_{\text{road}} \in V_{\text{road}}$. Different road segments $(v_{\text{road}}^a, v_{\text{road}}^b)$ are connected by edges $e_{\text{road}}^{ab} = (v_{\text{road}}^a, v_{\text{road}}^b, v_{\text{road}}^{ab}) \in E_{\text{road}}$. The respective edge attributes $e_{\text{road}}^{ab}$ indicate how two road segments are connected to each other. Two road segments can be located next to and behind each other, for instance at a road junction. In the latter case, the directed graph can clearly identify the predecessor and the successor. In addition, two lanes can cross or overlap each other, for instance at a road junction. Figure 1 shows an exemplary road network and the resulting road graph, where each elementary road segment is represented by a node. Each road segment in Figure 1a is shown as a node in Figure 1b. The segment A lies topologically next to segment B and goes in the same direction, therefore the corresponding nodes have an adjacent relationship. The elementary road segments A, B, G figuratively form a roadway. Thus, the corresponding nodes (A, B, G) in Figure 1b are connected with directed consecutive edges.

![Fig. 1: A geometric depiction of elementary road segments (A, B, C, D, E, F) defined by the lane boundaries (a). The resulting road graph of a). Possible relations (consecutive, adjacent, overlapping) are defined by edges between the road segments’ nodes (b).](image)

In addition to the road topology, traffic signs and the resulting traffic rules are of great importance. For example, it is important for a moving vehicle whether a heading traffic light is red or green. Information regarding the traffic rule situation is either deduced from the explicit or implicit road data (e.g. traffic signs, right of way, ...) or parsed from additional information sources (e.g. time-dependent signal phases for the traffic lights). This additional information is stored in combination with each regarding road segment.

### C. Spatial Abstraction

For the understanding of a traffic scene, the relative distances and velocities of the traffic participants, which influence each other’s behavior, are more important than the absolute poses in the Cartesian space. In the proposed approach, the traffic participants described by objects in Cartesian space are projected onto the Frenet space [24]. The road segments’ centerlines represent the curves. Consecutive road segments of a path in the road network are combined and represented by one curve.

The projection is the first phase in the process of combining the road topology and the object lists. Each traffic participant of a traffic scene $S_{\text{rgz}}(t)$ is individually assigned to an elementary road segment $a_i$, depending on its pose in space. Such an assignment is defined as a projection identity $m^i_a$. Since some spatial pieces of information are lost during projection, it must be ensured that all potentially relevant projection identities $m^i$ are considered in the case of ambiguous poses of a traffic participant $i$ (compare Figure 2). Depending on the position and orientation in relation to the respective road segment, a probability is estimated how well the actual pose of the traffic participant matches the lane. Assuming a traffic participant is in the lateral center of the road segment as well as perfectly aligned with its orientation, the estimated probability would be at maximum. To determine the probability of a projection identity $P(m^i_a)$, the Gaussian function can be used:

$$f_d(d_n) = \exp\left(-\frac{(d_n)^2}{2\sigma_d^2}\right), \quad (3)$$

$$f_p(\Phi) = \exp\left(-\frac{(\cos(\Phi) - 1)^2}{2\sigma_p^2}\right), \quad (4)$$

$$P(m^i_a) = f_d(d_n^i) \cdot f_p(\Phi^i). \quad (5)$$

$d_n^i$ and $\Phi^i$ describe the Euclidean distance of traffic participant $i$ to the centerline of the road segment $a$ and the angular deviation between its centerline and the orientation of the traffic participant. The standard deviations $\sigma_d$ and $\sigma_p$ allow the functions to be adapted to the problem.

In the shown example in Figure 2a, vehicle $i$ is displayed on top of three road segments (K, L, M). As shown in Figure 2b, each projection identity $m^i_{lk}$, $m^i_{lg}$, $m^i_{lm}$ is aligned with its respective track. The opacity indicates how high the matching probability is. Here, the vehicle $i$ is spatially farthest from the center line of M compared to the other tracks. In addition, the angular deviation is also largest here. Consequently, the matching probability is lowest in this case. All vehicles, such as cars, bicycles, trucks and motorcycles, are mapped to the tracks in the same way. Pedestrians, on the other hand, are projected onto nearby lanes regardless of their orientation. The motivation for this is that pedestrians rarely move, similar to vehicles, on and along the road, but cross it or walk on a nearby sidewalk. Therefore, they are mapped to the nearest
road segments to avoid neglecting them in the abstraction of
the environment.

The result of this projection is that each traffic participant \( i \) is linked to a set of elementary road segments by its projection identities \( m^i \) defined by \( \hat{\lambda}^i \).

\[ e \]

\[ \text{d) Creation of the Semantic Scene Graph} \]

In order to create significant relationships between individual traffic participants, their position in relation to other traffic participants is considered with respect to the road graph. The principals of these relation types are based on human behavior patterns. Semantic relationships, such as being in the same lane, the adjacent lane, parallel lane or in an intersecting lane, are the decisive factor. This information is already implicitly contained in the road graph in combination with the matched traffic participants. In this representation, however, it is decided to specify the relations explicitly. In addition to the current state of each traffic participant, possible routes are considered to determine the relations.

Figure 3a shows an exemplary projected traffic scene with five vehicles. Every vehicle, except vehicle 1 \((m^1, m^2, m^3)\), has only one projection identity for the sake of simplicity. A depiction of the resulting Semantic Scene Graph \( G_{\text{scene}} = (V_{\text{scene}}, E_{\text{scene}}) \) is shown in Figure 3b. In the following part, it is discussed how to specify different edge classifications \( \kappa_{\text{rel}} \). Furthermore, all attributes of an edge \( e_{\text{scene}} = (m^a_n, m^b_n) \) are described in detail.

\[ e_{\text{scene}} = \{ \kappa_{\text{rel}}, d_{\text{F}}, d_{\text{ip}}, a, d_{\text{n}}, \Phi, b, d_{\text{n}}, \Phi \} \] (6)

Multiple projection identities \( m^i \) are consolidated into the object node \( v^i_{\text{scene}} \), so that all edges also start and end from this node. This can result in parallel edges with different \( \kappa_{\text{rel}} \) and varying \( P(m^i) \) (see node 1 in Fig. 3b).

**Longitudinal Relation**

Let \( p^{ab} \) be a path in the road graph \( G_{\text{road}} \) between two road segments \( v^a_{\text{road}} \) and \( v^b_{\text{road}} \) (represented as nodes in the graph) on which there are two projection identities \( m^a_n, m^b_n \). If all edges of \( p^{ab} \) carry the attribute \( \kappa_{\text{rel}} = \text{consecutive} \), the two traffic participants \( i, j \) have a longitudinal relation with each other. As a result, an edge \( e^ij_{\text{scene}} \) between \( v^i_{\text{scene}} \) and \( v^j_{\text{scene}} \) can be spanned with the attribute semantic classification \( \kappa_{\text{rel}} = \text{longitudinal} \). These can be seen, for example, in Figure 3 between \( m^2_n \) and \( m^4_n \) (nodes 2 and 4). This means that the two traffic participants drive one behind another in one lane.

**Lateral Relation**

Vehicles traveling in adjacent lanes are connected in the scene graph with a lateral relationship. That means as soon as a path \( p^{ab} \) between \( v^a_{\text{road}} \) and \( v^b_{\text{road}} \) exists in \( G_{\text{road}} \), where each edge in \( p^{ab} \) has the attribute \( \kappa_{\text{rel}} = \text{consecutive} \) and exactly one edge \( \text{adjacent} \), those traffic participants in the scene graph carry the attribute \( \kappa_{\text{rel}} = \text{lateral} \) (see in Figure 3 node 1 and node 4). Lateral relationships are always bidirectional. This means, if in a directed graph there exists an edge \( e^ab_{\text{scene}} \) with a lateral attribute, there also exists an edge \( e^ba_{\text{scene}} \).

**Intersecting Relation**

Intersecting traffic participants \( i, j \) \((\kappa_{\text{rel}} = \text{intersecting})\) traveling in lanes that will overlap or merge. That means there exists a path \( p^{ab} \) where each edge of \( p^{ab} \) carries either the attributes \( \kappa_{\text{rel}} = \text{consecutive} \) or \( \text{adjacent} \) and exactly one edge carries the attribute \( \kappa_{\text{rel}} = \text{overlapping} \). Note that once an edge with the attribute \( \kappa_{\text{rel}} = \text{overlapping} \) is in \( p^{ab} \), all subsequent edges must be reversed. This is shown in the Figure 3 at node 1 and node 3. In the corresponding road network, parts of the road segments C and B lie geometrically on top of each other (see Figure 1). Looking at the path \( p^{AB} \) in the corresponding road graph, it can be noted that paths for ‘intersecting’ relations contain reverse-edges (e.g. \( e^{BA}_{\text{road}} \)).

In practical use, it sometimes makes sense to limit the length of the path \( |p| \). The number of edges as well as the attribute of the length of each edge can serve as a limit.

In the resulting semantic representation, only the traffic participant \( i \) is represented by a node \( v^i_{\text{scene}} \) in the scene graph \( G_{\text{scene}} \). The respective information of its projection identities \( m^i_n \) is stored in the edges. If the projection identities were to be chosen as separate nodes, the scene graph’s size would grow drastically, which would reduce the interpretability and inference of the graph. Furthermore, this maintains the affiliation of the projection identities to the actual traffic participant.

In addition to the semantic classification of the relations \( \kappa_{\text{rel}} \), important parameters are included as attributes in the edges. If the relation is not an intersecting one, the distance (in Frenet coordinates) \( d_{\text{F}} \) between both traffic participants’ projection identities \((m^i, m^j)\) is stored. Otherwise, the distance to the intersection point \( d_{\text{ip}} \) is calculated. It should be noted that \( d_{\text{F}} \) and \( d_{\text{ip}} \) can also be negative, since they are measured in the direction of travel.

For both \( m^a_n \) and \( m^b_n \) the distance \( d_{\text{n}} \) between the projected position and the original position is calculated. Additionally, the angular deviation \( \Phi \) between the traffic participant’s orientation and projection’s orientation are stored in \( e_{\text{scene}} \). Thus, for each relation, the distances of the projection identities (to the original traffic participant’s pose) and additionally the affiliation to each road segment \( a, b \) are provided by Equation 6.
IV. IMPLEMENTATION

The generation of the semantic scene graph $G_{scene}(t)$ for a timestamp $t$ from an object list consists of three steps.

For the calculation of the required distances and attributes, the open source libraries lanelet2 [25] or liblanlet [26] is used. The advantage of these libraries are that the map is already divided into road segments called lanelets. In addition, the map is stored directly in a road graph and the calculation of relations in chapter III can be applied directly to it.

First, the distance of all traffic participants $i \in I$ contained in the object list to all road segments is checked. A threshold value is specified in order to filter out non-relevant traffic participants ($I \rightarrow I', I' \subseteq I$), e.g. vehicles parked in parking lots or pedestrians who are far away. Subsequently, for all remaining $i \in I'$, all projection identities $m^i$ are estimated. This is done by comparing the center line of each road element of the road map with each pose $(x, y, \psi)$ of $\lambda'$ in $S_{3x2}$. The resulting projected states $\lambda'$ are stored as node elements in a graph structure. For larger maps, a subdivision of the scene into sub-scenes is recommended. Since the approach presented here is developed for the consideration of small, local traffic scenes, such as an intersection or highway entrance, the spatial subdivision of the map is not further considered. In the second step, the relations between all traffic participants are determined. To do so, for all $\lambda'$, all potential paths (routes the vehicle can take regarding its current position) are searched. Using a Dijkstra’s algorithm [27], possible paths $P_{road} \in P_{road}$ in $G_{road}$ (all $e_{road}$ should be treated as undirected edges, to also find reverse-edges) are searched. The sum of the lengths of the road elements in $P_{road}$ is chosen as cutoff distance. Then, all projection identities $m^i$ of $\lambda'$ are compared with all $m^j \notin \lambda'$. Assume $m^i$ and $m^j$ have the possible paths $P_{road}$ and $P_{road}'$. Whenever $b \in P_{road}$, a relation $e_{scene}$ is created. $\kappa_{rel}$ is determined using the conditions described in section III. In addition, to identify future intersecting paths, all road elements in $P_{road}$ are compared with $P_{road}'$ and checked for overlap. If this statement is true for any element, then $\kappa_{rel} = \text{intersecting}$.

To make the graph usable for other applications, it is exported to the dot language [28]. This interface enables data to be accessed easily from a wide variety of applications.

This can be used for example to analyze traffic scenes directly from the traffic simulator Carla [29].

For further data processing, it often makes sense to convert this information into numerical data. This is indispensable for creating datasets for machine learning approaches. For this purpose, the following file format, which is based on the TUDataset [30] is suggested for the graph information.

A. Graph Topology

Connections between nodes are specified by an $n \times n$ adjacency matrix $A$ ($n = |V_{scene}|$). If there exists an edge $e_{scene} = (m^i, m^j)$, $e_{scene} \in G_{scene}$ from node $v^i$ to node $v^j$, the entry at the $i$-th row and $j$-th column $A_{ij} = 1$. It makes sense to store the matrix $A$ in the coordinate format (COO) $A'$, because the description of parallel edges is easier using this format. $A'$ is a $n \times 2$ matrix, where each row contains both nodes ($v^i_{scene}, v^j_{scene}$) which are connected by an edge $e_{scene}$.

\[
A'_{k} = [v^i_{scene}, v^j_{scene}],
\]

where $k \in E_{scene}$, which also allows enumerating edges.

B. Node Attributes

The classification and the current state of a node $i$ is specified in a vector $u^i$ which is concatenated with all other vectors $u$ of the nodes of $V_{scene}$ which results in a $n \times |u|$ matrix $B$. The first entries of $u$ carry the information of the object’s classification $\kappa_{obj}$ in the shape of a one-hot encoding. The one-hot encoding function $\delta_{type}$ distinguishes between the classification type $type \in \{\text{car, pedestrian, bike, truck, other}\}$ of a the object. If, for example, an object $i$ is classified as a bike then $\delta_{\text{bike}}$ returns a 1:

\[
\delta_{\kappa_{obj}} = \begin{cases} 
1, & \text{if } \kappa_{obj} = \text{type}, \\
0, & \text{else} 
\end{cases}
\]

Furthermore, the absolute velocity $|\dot{x}_i, \dot{y}_i|$ of the object $i$ is added.

\[
B_i = u^i = [\delta_{\kappa_{obj}} \kappa_{obj}, \delta_{\text{pedestrian}} \kappa_{obj}, \delta_{\text{bike}} \kappa_{obj}, \delta_{\text{truck}} \kappa_{obj}, \delta_{\text{other}} \kappa_{obj}, |\dot{x}_i, \dot{y}_i|]
\]

C. Edge Attributes

An edge which connections are denoted by $A_{ij}$ are specified by the edge attribute matrix $C$ in the row $k$. Similar to the node attribute vector $u$, the edge attribute vector $C_k$ of $e_{scene} = (m^i, m^j)$ contains both classification and conditional information. The classification is described by a one-hot encoding defined by $\delta_{\kappa_{rel}}$ where $type \in \{\text{lon, lat, int}\}$ (compare Equation 8).

\[
C_k = [\delta_{\kappa_{rel}} \kappa_{rel}, \delta_{\text{lon}} \kappa_{rel}, \delta_{\text{lat}} \kappa_{rel}, \delta_{\text{int}} \kappa_{rel}, d_P, d_I, a, d_t, \Phi, b, d_t, \Phi]
\]

If the annotation of the road map contains traffic rules, it is also possible to encode, if a traffic participant (or projection identity) has to give way to the other traffic participant.
V. EVALUATION AND EXAMPLES

To evaluate the framework on real data, the INTERACTION dataset [23] was used.

A. Execution Time

In several cases a short execution time of the algorithm is crucial. In the following part, the results of the performance tests of the proposed framework are discussed. In Figure 4 the impact of both growing traffic scene in context of more entities and a larger road geometry is shown. The blue plot was created artificially. Here, entities were randomly created on a static street geometry, which have several projection identities and as many relationships with each other as possible. As the current implementation suggests, the calculation time grows quadratically with the number of entities (\(O(n^2)\)). The impact of the size of the road graph on the calculation time grows linearly by increasing the number of elementary road segments (\(O(n)\), here \(n\) is the number of elementary road segments). This timing factor can be neglected in contrast to the number of entities in the application. Most intersections of the evaluated scenarios of the INTERACTION dataset consist of between 14 and 100 elementary road segments. For larger maps, however, it is suggested, to divide them into sub-maps.

![Impact of the count of entities in a traffic scene with a fixed road geometry on the calculation time (blue, red)].(black). Impact of a larger road graph with a fixed number of entities (black).

The number of the entities in a single scene on the other hand limits the applicability of the framework in the context of real time usability. If we assume a repetition rate of the incoming object lists of 10 Hz (frame rate of the evaluation dataset), the calculation time should be less than 100 ms. This means on average there should not be more than 20\(^3\) entities in the scene to retain real time processing (see Figure 4).

This, however, was tested for the worst case, where the scene graph is quite dense, and each entity has several projection identities. The evaluation dataset contains scenes with up to 43 traffic participants. In general, the average calculation time is significantly lower than the worst case time (compare blue and red plot in Fig. 4). The highest value with 125 ms is for scenes with 43 traffic participants. Assuming that the dataset represents reality well, the limit of 100 ms set above would be fulfilled on average for all scenes with less than 40 traffic participants.

B. Completeness and Scalability

In this section, we will discuss when the semantic scene graph can be applied and when our model is incomplete.

Our model was applied to the entire INTERACTION dataset. A key feature of this dataset is that different intersection types and thus different road geometries were included. In our opinion, the dataset covers large parts of all possible traffic scenes.

| Intersection   | Roundabout | Merging |
|----------------|------------|---------|
| Nodes          | 5.71       | 4.99    | 4.42    |
| Edges per node | 1.9        | 1.25    | 3.54    |

TABLE II: Graph statistics of different intersection types

The table Table II shows the average nodes and edges per node of the semantic scene graph for each intersection type in the dataset. Here, differences between the intersection types can be seen. The roundabout differs only slightly from the intersection in the average number of edges. In intersections, parallel lanes exist more often and thus traffic participants can have more relationships with near vehicles. Most of the merging scenes of the dataset included scenes from a multi-lane roadway. Thus, many lateral relations are included and semantic scenes graphs contain on average more edges per node.

In principle, the average number of nodes can only indicate the size of the traffic scene, but it cannot make a concrete difference about how crowded or wide an intersection area is.

In addition, the completeness of the scenes was evaluated. The number of traffic participants in the original scene was compared with the number of nodes in the corresponding semantic scene graph. In the dataset examined, over 99.9% of the scenes were depicted realistically. However, the individual exceptions point out the weaknesses of the scene graph model: In Figure 5 an invalid traffic scene is depicted. Here, the vehicle with the ID 41 was not translated to the semantic scene graph. The reason for this is that this vehicle is too far away from the actual road and therefore cannot be assigned to any lane. In general, the matching distance could be increased, but this would result in too many irrelevant lanes being taken into account for other vehicles, which would increase the calculation time and also make the graph too confusing.

Such scenes can be caused by counting errors (probable cause of the scene in Figure 5) but also by behavior of traffic participants that do not comply with traffic rules. An example
for this can be an obstacle on the roadway that can only be avoided by changing to the sidewalk or the oncoming lane.

As a consequence, the model can only describe traffic scenes that correspond to the traffic rules. The corner cases described above cannot be described correctly in the semantic scene graph. A temporal consideration of several successive scenes, however, could improve the completeness.

C. Situation-specific Analysis

In this section, the generated semantic scene graphs are discussed in depth using two use scenes.

Figure 6 shows two exemplary traffic scenes in both the scene graph representation and the bird’s eye view. For a clearer visualization, the two mutual intersecting relationships between two entities have been represented as one bilateral edge in this figure. Furthermore, the cutoff-distance is set to 30 m. The first traffic scene (Figure 6a) shows several vehicles entering a roundabout. On the right-hand side, five vehicles are driving behind each other and the first has just entered the roundabout. This vehicle group (13,14,15,17,18) is highlighted in the graph by a darker blue color. This group can be separated in the graph by only checking for successive longitudinal relations. Strictly speaking, the vehicle with the ID 10 should also be added to this group, but since this vehicle has no other intersecting relation with another group (3,16), this vehicle can count as an extra group. This allows relevant traffic participants to be clustered only by the way they relate to each other, for example to distinguish different traffic situations [4] from each other. Figure 6b shows a second traffic scene at a different place with different road geometry. Although at first glance the scenes are clearly different, both in terms of road geometry and the position of the traffic participants. But looking at the graph, similarities can be identified. In both graphs, there are three different groups of traffic participants. One group that enters the intersection area (darker blue) and a second group that can/will cross this area (green). Then the last group that has already left the intersection area (light blue). This example shows that using the generic description of the Semantic Scene Graph, two different traffic scenes can be compared with each other. It could be shown that the topology of the traffic scene was transferred in a certain form into the graph structure. It should be noted here that the traffic scene is described solely by the interaction between different traffic participants and on the basis of their current motion state. Accordingly, this scene description cannot be used to explicitly describe special road (geometry) conditions or, for example, blind spots.

Fig. 6: Two exemplary traffic scenes at different road geometries (bottom) and the corresponding Semantic Scene Graphs (top). Nodes have been colored to improve the visualization of groups.

VI. Conclusion and Outlook

The differentiation and the description of various traffic scenes with regard to the verification and validation of automated driving functions is a crucial factor. In this work, we have proposed a concept to describe traffic scenes in the context of machine readability and how to implement the said model. Our Semantic Scene Graph model makes it possible to compare traffic scenes with different conditions using a universal graph representation.

The model projects traffic participants on roads and uses the road networks´ topology to create a corresponding graph of the scene. Relations between the traffic participants are denoted as edges with multiple attributes. Due to the clearly defined state space of a scene (compare $X'$ and $\varepsilon_{scene}$), this abstraction of a rather complex scenario promises to give a better inference between input data and result in a subsequent machine learning architecture, than a raw object list as training data, since interactions between traffic participants are denoted explicitly. Furthermore, a format is provided which represents the above-mentioned scene description in a machine-readable format and thus opens up the possibility for analysis using machine learning methods.

Since we designed our concept to be used in machine learning applications, we are going to use GNN to cluster and predict traffic scenes. In future work, the proposed framework has to be applied on traffic datasets [23] [3] [22] and the resulting Semantic Scene Graphs should be used to classify and cluster different traffic scenes, which leads to a more detailed evaluation of the model.
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REFERENCES

[1] A. Pretschner, F. Hauer, and T. Schmidt, “Tests für automatisierte und autonome Fahrsysteme: Wiederverwendung aufgezeichneter Fahrten ist nicht rechtfertigt,” Informatik Spektrum, vol. 44, no. 3, pp. 214–218, 2021. [Online]. Available: https://link.springer.com/10.1007/s00287-021-01364-w

[2] W. Wachenfeld and H. Winner, “The Release of Autonomous Vehicles,” in Autonomous Driving, M. Maurer, J. C. Gerdes, B. Lenz, and H. Winner, Eds. Springer Berlin Heidelberg, 2016, pp. 425–449. [Online]. Available: http://link.springer.com/10.1007/978-3-662-48847-8_21

[3] M. Zipf, T. Fleck, M. R. Zofka, and J. M. Zöllner, “From Traffic Sensor Data To Semantic Traffic Descriptions: The Test Area Autonomous Driving Baden-Württemberg Dataset (TAF-BW Dataset),” in 2020 IEEE 21st International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2020, pp. 1–7. [Online]. Available: https://ieeexplore.ieee.org/document/9294539/

[4] S. Ulbrich, T. Menzel, A. Reschka, F. Schultdt, and M. Maurer, “Defining and Substantiating the Terms Scene, Situation, and Scenario for Automated Driving,” in 2015 IEEE 18th International Conference on Intelligent Transportation Systems, 2015, pp. 982–988.

[5] D. Bogdoll, J. Breitenstein, F. Heidecker, M. Bieshaar, B. Sick, T. Fingscheidt, and J. M. Zöllner, “Description of Corner Cases in Automated Driving: Goals and Challenges,” 2021.

[6] W. Damm, S. Kemper, E. Möhlmann, T. Peikenkamp, and A. Rakow, “Using Traffic Sequence Charts for the Definition of HAVs,” in European Congress on Embedded Real Time Software and Systems 2018, ser. 9th European Congress on Embedded Real Time Software and Systems (ERTS 2018), 2018, inproceedings. [Online]. Available: https://hal.archives-ouvertes.fr/hal-01714066v1/file/ERTS_2018_paper_17.pdf

[7] E. de Gelder, J.-P. Paardekooper, A. K. Saberi, H. Eltouﬁ, O. O. d. Camp., S. Kaines, J. Ploeg, and B. De Schutter, “Towards an Ontology for Scenario Deﬁnition for the Assessment of Automated Vehicles: An Object-Oriented Framework,” arXiv:2001.11507 [cs], Dec. 2021, arXiv: 2001.11507. [Online]. Available: http://arxiv.org/abs/2001.11507

[8] G. Bagschik, T. Menzel, and M. Maurer, “Ontology-based Scene Creation for the Development of Automated Vehicles,” arXiv:1704.01006 [cs], 2018. [Online]. Available: http://arxiv.org/abs/1704.01006

[9] S. Ulbrich, T. Nothdurft, M. Maurer, and P. Hecker, “Graph-based context representation, environment modeling and information aggregation for automated driving,” in 2014 IEEE Intelligent Vehicles Symposium Proceedings. IEEE, 2014, pp. 541–547. [Online]. Available: http://ieeexplore.ieee.org/document/6856565/

[10] G. Antoniou and F. V. Harmelen, “Web Ontology Language: OWL,” in Handbook on Ontologies, 2004.

[11] F. Schultdt, “Ein Beitrag für den methodischen Test von automatisierten Fahrfunktionen mit Hilfe von virtuellen Umgebungen,” 2017.

[12] W. Chen and L. Klou, “An Ontology-based Approach to Generate the Advanced Driver Assistance Use Cases of Highway Traffic,” in Proceedings of the 10th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management. SCITEPRESS - Science and Technology Publications, 2018, pp. 75–83. [Online]. Available: http://www.scitepress.org/DigitalLibrary/Link.aspx?doi=10.5220/0006931700750083

[13] L. Zhao, R. Ichise, Z. Liu, S. Mitu, and Y. Sasaki, “Ontology-Based Driving Decision Making: A Feasibility Study at Uncontrolled Intersections,” IEECE Transactions on Information and Systems, vol. E100-D, no. 7, pp. 1425–1439, 2017. [Online]. Available: https://www.jstage.jst.go.jp/article/transinfo/E100.D/7/E100.D_2016DP7337/article

[14] L. Huang, H. Liang, B. Yu, B. Li, and H. Zhu, “Ontology-Based Driving Scene Modeling, Situation Assessment and Decision Making for Autonomous Vehicles,” in 2019 4th Asia-Paciﬁc Conference on Intelligent Robot Systems (ACIRS). IEEE, 2019, pp. 57–62. [Online]. Available: https://ieeexplore.ieee.org/doi/10.1109/ACIRS.2019.8935984

[15] R. Kohlhaas, T. Bittner, T. Schamm, and J. M. Zöllner, “Semantic state space for high-level maneuver planning in structured trafﬁc scenes,” in 17th International IEEE Conference on Intelligent Transportation Systems (ITSC). IEEE, 2014, pp. 1060–1065. [Online]. Available: http://ieeexplore.ieee.org/document/6957828/

[16] A. Armand, D. Filliat, and J. Ibanez-Guzman, “Ontology-based context awareness for driving assistance systems,” in 2014 IEEE Intelligent Vehicles Symposium Proceedings. IEEE, 2014, pp. 227–233. [Online]. Available: http://ieeexplore.ieee.org/document/6856569/

[17] D. Petrich, D. Azarfar, F. Kuhn't, and J. M. Zöllner, “The Fingerprint of a Traffic Situation: A Semantic Relationship Tensor for Situation Description and Awareness,” in 2018 21st International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2018, pp. 429–435. [Online]. Available: https://ieeexplore.ieee.org/document/8569611/

[18] J. Gao, C. Sun, H. Zhao, Y. Shen, D. Angelov, C. Li, and C. Schmid, “VectorNet: Encoding HD Maps and Agent Dynamics from Vectorized Representation,” arXiv:2005.04259 [cs, stat], May 2020, arXiv: 2005.04259. [Online]. Available: http://arxiv.org/abs/2005.04259

[19] H. Zhao, J. Gao, T. Lan, C. Sun, B. Sapp, B. Varadarajan, Y. Shen, Y. Shen, Y. Chai, C. Schmid, C. Li, and D. Angelov, “TNT: Target-driveTrajectory Prediction,” 2020.

[20] F. Diehl, T. Brunner, M. T. Le, and A. Knoll, “Graph Neural Networks for Modelling Traffic Participant Interaction,” 2019. [Online]. Available: http://arxiv.org/abs/1903.01254

[21] H. Ma, Y. Sun, J. Li, and M. Tomizuka, “Multi-Agent Driving Behavior Prediction across Different Scenarios with Self-Supervised Domain Knowledge,” p. 8.

[22] J. Bock, R. Krajewski, T. Moers, S. Runde, L. Vater, and L. Eckstein, “The inD Dataset: A Drone Dataset of Naturalistic Road User Trajectories at German Intersections,” 2019. [Online]. Available: http://arxiv.org/abs/1911.07602

[23] W. Zhan, L. Sun, D. Wang, H. Shi, A. Clausse, M. Naumann, J. Kummerle, H. Königshof, C. Stiller, A. de La Fortelle, and M. Tomizuka, “INTERACTION Dataset: An INTERNational, Adversarial and Cooperative moTION Dataset in Interactive Driving Scenarios with Semantic Maps,” 2019. [Online]. Available: http://arxiv.org/abs/1910.03088

[24] “Frenet–Serret formulas,” Sept 2021. [Online]. Available: https://en.wikipedia.org/wiki/Frenet%E2%80%93Serret_formulas

[25] F. Poggemans, J.-H. Pauls, J. Janosovits, S. Orf, M. Naumann, F. Kuhn't, and M. Mayr, “Lanee:2: A High-Definition Map Framework for the Future of Automated Driving,” in Proc. IEEE Intl. Trans. Sys. Conf., Hawaii, USA, November 2018. [Online]. Available: http://www.nrt.kit.edu/jz/public/download/2018/Poggemans2018Laeneet2.pdf

[26] P. Bender, J. Ziegler, and C. Stiller, “Lanelets: Efficient map representation for autonomous driving,” 2014 IEEE Intelligent Vehicles Symposium Proceedings, pp. 420–425, 2014.

[27] “Dijkstra’s algorithm,” Aug 2021. [Online]. Available: https://en.wikipedia.org/wiki/Dijkstra%27s_algorithm

[28] “Dot language,” Aug 2021. [Online]. Available: https://graphviz.org/doc/info/lang.html

[29] L. Tötte, M. Zipf, D. Bogdoll, M. R. Zofka, and J. M. Zöllner, “Reliving the Dataset: Combining the Visualization of Road Users’ Interactions with Scenario Reconstruction in Virtual Reality,” 2021. [Online]. Available: http://arxiv.org/abs/2105.01610

[30] C. Morris, N. M. Kriege, F. Bause, K. Kersting, P. Mutzel, and M. Neumann, “TU-Dataset: A collection of benchmark datasets for learning with graphs,” p. 10, 2020.