Integrating Road Surface Condition Data into OpenDRIVE Models for Autonomous Vehicle Simulations

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Abstract

ASAM OpenDRIVE is widely used as a standardized geometric road network description format supporting simulation-based development of advanced driver assistance and autonomous driving systems. While the standard primarily focuses on static road geometry and topology, the increasing need for realistic simulation inputs highlights the importance of incorporating empirically observed pavement conditions into digital road models. This paper proposes a conceptual framework for integrating automatically detected pavement defects into OpenDRIVE without introducing any schema extensions. Road surface anomalies identified from smartphone-based image acquisition using deep neural networks (DNN) are represented as JSON-based intermediate data and transformed by a dedicated mapping module into OpenDRIVE-compliant structures. The approach formalizes the geometric transformation from WGS84 coordinates to the OpenDRIVE curvilinear reference system and encodes defects either as discrete object-level entities or as lane-level material modifications along the road reference line. The main contribution lies in demonstrating that OpenDRIVE, although originally conceived as a geometric exchange format, inherently supports condition-aware road modeling when its existing hierarchical elements are used consistently. The proposed integration pathway establishes a structured link between perception-level data acquisition and simulation-compatible digital road descriptions, thereby contributing to more realistic and context-aware virtual testing environments.

1. Introduction

ASAM OpenDRIVE is an open format specification designed to provide a standardized description of road network logic for driving simulation applications. Established as an industry standard under the Association for Standardization of Automation and Measuring Systems (ASAM), OpenDRIVE addresses the critical need for interoperability between different simulation platforms used in the development and validation of Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) functions (ASAM e.V., 2021, ASAM e.V., 2024a, ASAM e.V., 2024b). The standard employs Extensible Markup Language (XML) syntax with the .xodr file extension to encode comprehensive road network descriptions that encompass road geometry, lane configurations, junction topologies, traffic infrastructure elements such as signals and signs, and various roadside objects (Bray et al., 2008).
A fundamental architectural principle of OpenDRIVE is the reference line concept, whereby each road segment is defined along a central reference line to which all geometric and semantic attributes are parametrically attached using a curvilinear coordinate system. The standard is specifically designed to describe static road network elements, deliberately excluding dynamic content such as vehicle maneuvers or traffic scenarios, which are instead addressed by complementary standards within the ASAM simulation ecosystem, particularly ASAM OpenSCENARIO (ASAM e.V., 2024c) for dynamic scenario specification and ASAM OpenCRG (ASAM e.V., 2019) for high-resolution road surface descriptions. Road networks described in OpenDRIVE can be either synthetically generated for theoretical testing purposes or derived from real-world data through surveying and mapping processes, enabling validation activities that span from early-stage algorithm development through hardware-in-the-loop testing.

The adoption of OpenDRIVE as a common exchange format facilitates collaborative development across the automotive industry, allowing manufacturers, suppliers, simulation tool vendors, and research institutions to share road network data and simulation scenarios while ensuring consistency and reproducibility across different development and testing environments.

OpenDRIVE was originally developed to provide a standardized geometric and topological description of road networks in support of driving simulations. Its primary purpose is to ensure interoperability between simulation platforms by offering a consistent representation of static road infrastructure. In this study, we do not focus on simulation itself, but on its prerequisite: the structured provision of realistic road surface condition data that can enhance simulation fidelity.

Although OpenDRIVE is typically interpreted as a geometric road model, its hierarchical structure – including road-level surface elements, object-level attachments, and lane-level material definitions – implicitly enables the representation of condition-aware attributes. While the model is fundamentally defined in a local coordinate system, it can be placed into a global spatial reference framework through the use of the `<geoReference>` tag. When these elements are used in a coordinated manner, OpenDRIVE can evolve from a purely geometric description into a condition-aware road model. In this sense, the standard has the potential to serve as a foundation for digital road twin concepts, where geometric structure and operational pavement state coexist within a unified framework.

This paper advances the following conceptual proposition: OpenDRIVE is inherently capable of supporting condition-aware road modeling without requiring formal standard

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extensions, provided that automatically detected pavement defects are systematically mapped onto its existing object- and material-level structures.
Accordingly, the research question addressed in this study is: how can road surface defects detected from mobile camera imagery using deep neural networks (DNN) be transformed into structurally consistent and simulation-compatible OpenDRIVE representations?

To answer this question, we outline a conceptual integration framework that links smartphone-based image acquisition and deep learning-based defect detection with standardized OpenDRIVE encoding strategies. The proposed approach demonstrates how georeferenced defect information can be incorporated either as discrete road objects or as lane-level material modifications along the parametric reference line, thereby enriching OpenDRIVE models with empirically derived surface condition data.

2. Road Surface Description in OpenDRIVE

The ASAM OpenDRIVE standard provides a comprehensive framework for describing static road network elements for driving simulation, with a particular emphasis on the geometric and physical properties of road surfaces. The standard’s capabilities operate through a hierarchical structure primarily encompassing road and lane levels, while providing the flexibility to incorporate object-level specifications for localized features, thereby offering multiple methodologies for representing surface conditions with varying precision.

At the road level, OpenDRIVE implements surface description through the <surface> element, positioned as a child of the <road> element. This structure enables the specification of properties affecting the entire road width or significant longitudinal sections. This road-level description serves as the primary mechanism for integrating high-resolution data via native support for the OpenCRG format, an architectural decision that separates macroscopic road network topology from microscopic surface characteristics. The <surface> element contains one or more <CRG> child elements which reference external files using a curved regular grid aligned with the road’s reference line. These elements are defined along the *s*-coordinate using sStart and sEnd attributes, allowing for varying surface conditions longitudinally. Furthermore, three attachment modes provide the necessary flexibility to integrate measured data while maintaining geometric consistency with the underlying road reference line.

A significant enhancement introduced in version 1.7.0 addresses the efficient representation of localized features by nesting a <surface> element within an <object> element. This allows OpenDRIVE to associate high-resolution data with discrete entities such as manhole covers, road patches, or localized irregularities, overcoming the computational inefficiency of high-resolution modeling for the entire road when detail is only required for spatially discrete features. In this context, the object’s surface height is additively combined with the road surface height, enabling a layered representation that is particularly relevant for high-fidelity tire-road interaction and vehicle dynamics simulation. Complementing these high-resolution methods, OpenDRIVE provides lane-level capabilities through the <material> element located within individual <lane> elements. While the CRG approach emphasizes geometry, the lane material specification focuses on physical attributes such as the surface type, the (measured) friction coefficient, and the roughness of the surface. These specifications are defined relative to the *s*-coordinate via the mandatory sOffset attribute, where a definition remains valid until superseded by a subsequent <material> element or the end of the lane section.

To ensure a deterministic simulation environment, OpenDRIVE implements a strict hierarchical precedence mechanism. When a road-level <CRG> element is defined with the purpose="friction" attribute, its values supersede any friction specifications made within lane-level <material> elements for that specific spatial extent. This precedence ensures that high-resolution measured data takes priority over parameterized material properties. Furthermore, if multiple <CRG> entries define the same physical property at a given location, the last entry in the sequence of occurrence within the XML file shall be used, implementing a last-write-wins semantic for data precedence resolution. However, the present study focuses exclusively on object- and lane-level representations.

3. State-of-the-Art Overview of Road Surface Condition Data Models

The assessment of road surface condition has evolved from manual inspection to sensor-based and data-driven frameworks supporting pavement management and Intelligent Transport Systems. International standards provide the methodological backbone of these approaches. ASTM D6433-07 defines the Pavement Condition Index (PCI) for systematic distress evaluation (ASTM International, 2007), while the FHWA LTPP Manual specifies detailed distress taxonomies and severity criteria (FHWA, 2014). In Europe, RVS 13.01.16 and the Austrian PMS Handbook establish structured classification and lifecycle-oriented maintenance principles (FSV, 2013; PMS Consult et al., 2016). Broader methodological foundations addressing surface texture, drainage, and vehicle-pavement interaction were provided by COST 354 (COST 354, 2006), and standardized data quality procedures are defined by EuroRAP (EuroRAP, 2018).

Recent initiatives extend these standards toward digital and AI-based implementations. The BORIS project introduced automated crack detection using image-based machine learning (AIT Austrian Institute of Technology and ASFINAG and Federal Ministry for Climate Action, 2024), while ESRIUM integrates mobile mapping and multi-sensor fusion for digital road wear mapping (JOANNEUM RESEARCH et al., 2023). Empirical research further demonstrates strong links between pavement condition and traffic safety: elevated IRI values, increased roughness, rut depth, and reduced friction significantly correlate with higher crash risk (Solanke and Gandole, 2023, Parsa, 2020, Lebaku et al., 2025). These findings highlight the need for condition-aware frameworks that integrate surface characteristics into safety-oriented road management and simulation environments.

4. Data Sources and a Possible Processing Pipeline

The evolution of pavement distress detection methodologies has been fundamentally shaped by advances in sensor technology and data acquisition platforms, resulting in diverse survey techniques that vary substantially in spatial resolution, operational cost, and deployment scalability. Ground-based mobile mapping systems represent the most widely deployed professional survey infrastructure, integrating terrestrial laser scanning (TLS) or mobile laser scanning (MLS) units with synchronized imaging sensors, GNSS, and IMU to produce georeferenced three-dimensional point clouds and high-resolution imagery of road surfaces (Guan et al., 2015). These systems, exemplified by commercial platforms manufactured by Leica Geosystems and Trimble, achieve point densities exceeding 150,000 points per square meter with sub-centimeter positioning accuracy, enabling precise geometric characterization of surface distresses including rutting depths, crack widths, and pothole volumes (Kumar et al., 2015). The LiDAR-based approach offers particular advantages in capturing elevation-based distresses where millimeter-scale vertical accuracy is essential, and demonstrates robustness to lighting variations that commonly degrade image-based detection systems (Tsai and Li, 2012). However, capital investment requirements for professional-grade mobile mapping systems, typically ranging from several hundred thousand to over one million US dollars, combined with specialized expertise requirements for data processing, have historically limited deployment to well-funded road agencies, thereby constraining spatial and temporal coverage achievable within budgetary constraints (Zhang et al., 2017)

In response to cost and scalability limitations, recent research has increasingly explored alternative data acquisition paradigms leveraging consumer-grade sensors and crowdsourced data collection frameworks. Unmanned Aerial Vehicles (UAVs) equipped with imaging sensors and solid-state LiDAR units have emerged as viable platforms for targeted pavement surveys, particularly for rapid assessment of specific segments or areas with restricted ground access (Hoang and Nguyen, 2019). More transformative has been the development of smartphone-based and dashcam-enabled pavement monitoring systems, which exploit ubiquitous deployment of consumer mobile devices equipped with accelerometers, gyroscopes, GNSS receivers, and camera systems to enable participatory sensing approaches where ordinary road users contribute data passively during routine travel (Eriksson et al., 2008, Seraj et al., 2016). These crowdsourcing methodologies generate spatially extensive datasets at unprecedented scales, albeit at the cost of reduced measurement precision, heterogeneous sensor specifications, and increased signal noise attributable to variations in vehicle suspension characteristics (Mednis et al., 2011). The extraction of meaningful pavement condition indicators from smartphone accelerometer data requires sophisticated signal processing including filtering and vehicle dynamics compensation, while dashcam imagery analysis depends fundamentally on advances in computer vision and deep learning, particularly convolutional neural network (CNN) architectures such as YOLO, Faster R-CNN, and MobileNet variants (Maeda et al., 2018, Zhang et al., 2016). Contemporary research has demonstrated that properly trained deep learning models can achieve detection accuracies exceeding 85% for major distress categories including longitudinal and transverse cracking, alligator cracking, and potholes when evaluated against ground-truth annotations (Gopalakrishnan et al., 2017), though performance degrades significantly for subtle distresses such as hairline cracks that lack sufficient visual contrast in wide-angle dashcam perspectives. Traditional surveying techniques employing total stations, differential GNSS, and digital levels remain relevant for establishing ground-truth reference datasets and conducting detailed geometric characterization where centimeter-level accuracy is required (McGhee, 2004).

Figure 1. Road damage detected using a deep neural net (DNN) evaluation of mobile phone camera imagery

The methodology presented by Horvath and Barsi establishes a practical framework for acquiring pavement distress data through smartphone-based image collection and automated processing using convolutional neural networks, providing spatially referenced defect information suitable for subsequent integration into OpenDRIVE road network models (Horvath and Barsi, 2025). The approach leverages pre-trained deep learning models originally developed by Maeda et al. at the University of Tokyo, which were trained to detect and classify eight categories of road damage defined in the 2013 Japanese Road Maintenance and Repair Guidebook (Maeda et al., 2018). The system architecture comprises two primary components: a mobile Android application that captures geotagged imagery during field surveys and performs real-time inference at approximately 9-10 frames per second, and a backend data management infrastructure that stores detected defects with their spatial coordinates, damage type classifications, confidence scores, and bounding box parameters in a structured SQL database format (Fig. 1). The field data collection workflow employs standard consumer smartphones equipped with integrated cameras and GNSS receivers, enabling cost-effective participatory sensing approaches where surveyors – either pedestrian or vehicle-mounted – capture continuous video streams of road surfaces under natural lighting conditions without requiring specialized equipment or extensive operator training; however, linking the recorded positions from the phone’s GNSS to the map reference system typically requires either positional corrections or contextual interpretation.

The detection pipeline implements object recognition through transfer learning, utilizing MobileNet-based feature extraction architectures optimized for mobile deployment, wherein input image frames undergo preprocessing, convolutional feature extraction, region proposal generation, and classification with associated confidence scoring. Validation testing conducted on a representative urban road segment in Budapest’s 11th district, characterized by high defect density within a spatially compact area, demonstrated that the system successfully detected 9 out of 17 visually identifiable pavement distresses when operating with a 40% confidence threshold, while also generating six false positive detections primarily associated with non-pavement surface features including manhole covers, paving stone speed humps, and textured entry zones. The georeferenced output data structure, which associates each detection with WGS84 geographic coordinates, damage type classification codes, confidence metrics, and pixel-space bounding box coordinates,

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provides fundamental attributes necessary for populating OpenDRIVE lane-level or object-level surface condition descriptors. The methodology demonstrates particular relevance for augmenting OpenDRIVE models with empirically derived pavement condition data by enabling systematic conversion of detected defects into standardized road surface representations: localized damage features such as potholes, patches, and crack clusters can be encoded as discrete road objects with associated surface elevation or material property descriptors, while distributed deterioration patterns including longitudinal cracking, rutting, and linear crack propagation can inform lane-level material friction and roughness attributes along the s-coordinate parametrization of the road reference line. This approach establishes a scalable data acquisition pathway that bridges field observation with standardized digital road network description, facilitating the population of context-aware surface condition databases that support both infrastructure asset management and intelligent transport system applications requiring high-fidelity representations of actual pavement states.

5. Conceptual Integration Framework: Mapping DNN-Detected Defects to OpenDRIVE

This section presents a concise conceptual framework for integrating automatically detected pavement defects into OpenDRIVE models. No modification or extension of the OpenDRIVE standard is proposed. Instead, the approach relies exclusively on a consistent use of existing lane-level and object-level elements, thereby supporting the central proposition introduced earlier: OpenDRIVE can function as a condition-aware road model when its current structures are semantically coordinated.

In this concept, CRG-based high-resolution surface modeling is intentionally omitted. The mobile camera-based DNN pipeline primarily delivers defect type and georeferenced location, but not dense elevation fields. Therefore, integration is limited to lane-level material encoding for distributed condition changes and object-level encoding for localized defects.

5.1 System Architecture and Data Flow

The DNN pipeline produces detection results in JSON-based intermediate representation, containing defect class, confidence, bounding box, timestamp, and GNSS position (WGS84), optionally complemented by device orientation (Fig. 2).

A dedicated mapping module transforms these JSON detections into OpenDRIVE-compliant structures by converting the detection geometry into OpenDRIVE road coordinates (s, t), mapping defect semantics to either lane material updates or discrete objects, and aggregating repeated observations.

5.2 Lane-Level Representation

Distributed deterioration patterns (e.g., persistent cracking interpreted as increased roughness) can be encoded as longitudinal material changes along the lane’s s-coordinate. The mapping module aggregates detections over a segment and updates friction or roughness parameters accordingly.

Here, observations within the segment triggered a reduced friction value and increased roughness. This remains fully compliant with standard OpenDRIVE lane semantics.

Listing 1. Lane-level material encoding example

```xml
<lane id="-1" type="driving" level="false">
    <material sOffset="120.0"
    surface="asphalt"
    friction="0.65"
    roughness="0.10"/>
</lane>
```

5.3 Object-Level Representation

Localized defects (e.g., potholes, patches) are encoded as <object> elements positioned at specific (s, t) coordinates relative to the road reference line.

Listing 2. Object-level defect encoding example

```xml
<object id="1001"
    name="pothole"
    type="surfaceDefect"
    s="125.40" t="-1.20"
    hdg="0.02"
    length="0.60"
    width="0.45"
    height="0.08">
    <userData code="dnn">
        <vector name="confidence"
        value="0.87"/>
    </userData>
</object>
```

The heading (hdg) is typically aligned with the reference line direction at the placement location. Optional <userData> elements preserve provenance and confidence without altering the schema.

If a footprint approximation is desired, an object-local outline can be defined using (u, v) coordinates in the object’s local frame.

5.4 Geometric Localization: From WGS84 to OpenDRIVE

The key technical step of the integration framework is the transformation of detected defects from the mobile sensing domain into OpenDRIVE road coordinates. The DNN output provides image-space bounding boxes together with GNSS-based device positions in WGS84 coordinates and, optionally, device orientation. To localize a defect in the OpenDRIVE model, a multi-stage coordinate transformation is required.

First, the ground position of the detected defect is estimated. Under a road-plane assumption, a viewing ray is constructed from the camera center through the bounding box (typically using the lower center point as ground contact proxy). Using device position and orientation, this ray is intersected with the assumed road surface, yielding a three-dimensional defect position expressed in WGS84 coordinates. Where detailed camera calibration is unavailable, a simplified monocular approximation may be applied, accepting reduced metric accuracy while relying on spatial aggregation over repeated observations.

Second, the geodetic coordinates are transformed into the same projected metric coordinate system in which the OpenDRIVE

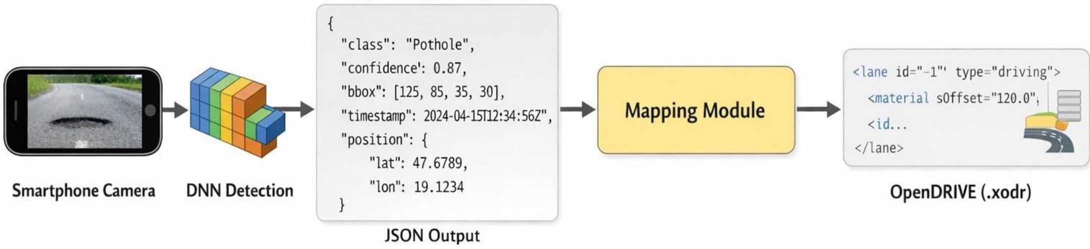

Figure 2. System architecture of the proposed integration workflow from mobile perception to OpenDRIVE encoding

model is defined. This ensures consistency between the detected defect location and the reference line geometry stored in the planView definition.

Third, the defect point is projected onto the closest location of the OpenDRIVE road reference line. The longitudinal coordinate s is computed as the accumulated arc length from the beginning of the road to the projection point. The lateral coordinate t is calculated as the signed perpendicular distance between the defect position and the reference line at that location. The sign convention follows OpenDRIVE’s standard definition relative to the reference line orientation.

Optionally, the computed (s, t) pair can be used to determine the affected lane by evaluating lane width definitions at the corresponding s position. For object-level encoding, the object heading is typically aligned with the reference line direction at the projection point. If geometric dimensions are available or estimated, they define the defect footprint in the object’s local (u, v) coordinate system, oriented by the assigned heading.

6. Conclusions and Future Work

This paper presented a conceptual framework for integrating automatically detected pavement defects into ASAM OpenDRIVE road models without introducing any modification or extension to the standard. Rather than proposing new schema elements, the study demonstrated that condition-aware road modeling can be achieved through a consistent and semantically coordinated use of existing lane-level material definitions and object-level elements.

The proposed integration workflow links smartphone-based image acquisition and deep neural network-based defect detection to OpenDRIVE representations via a dedicated mapping module. By transforming georeferenced defect information from WGS84 coordinates into the OpenDRIVE curvilinear reference system (s, t), localized defects can be encoded as discrete road objects, while distributed deterioration patterns can be represented through longitudinal lane material updates. This establishes a structured pathway from field-level perception data to simulation-compatible road network descriptions.

The primary contribution of this work lies in the formalization of this mapping concept. To the best of our knowledge, OpenDRIVE is not currently used in practice for systematic encoding of empirically derived pavement condition data. The presented framework demonstrates that the standard, although originally conceived as a geometric road model for simulation interoperability, inherently supports condition-aware representations when its hierarchical structure is appropriately utilized. In this sense, OpenDRIVE can serve not only as a geometric exchange format, but also as a carrier of enriched infrastructure state information, moving it conceptually closer to digital road twin applications.

Several limitations remain. The current concept does not incorporate high-resolution elevation modeling (e.g., CRG-based surface descriptions), and geometric localization relies on monocular camera assumptions that may introduce positional uncertainty. Furthermore, no direct validation within a specific driving simulator environment has yet been performed to quantify the impact of the proposed encoding on vehicle dynamics or ADAS performance.

Future work will therefore focus on (i) systematic evaluation of localization accuracy and its influence on object placement reliability, (ii) integration and testing within selected simulation environments to assess behavioral sensitivity to encoded surface defects, and (iii) exploration of extended perception inputs, including multi-sensor fusion, to improve geometric fidelity. Through these steps, the proposed concept may contribute to bridging pavement condition assessment and simulation-based validation workflows in a unified digital infrastructure modeling framework.

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