OSDaR23: Open Sensor Data for Rail 2023

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Abstract— **For driverless train operation on mainline railways, several tasks need to be implemented by technical systems. One of the most challenging tasks is to monitor the train's driveway and its surroundings for potential obstacles due to long braking distances. Machine learning algorithms can be used to analyze data from vision sensors such as infrared (IR) and visual (RGB) cameras, lidars, and radars to detect objects. Such algorithms require large amounts of annotated data from objects in the rail environment that may pose potential obstacles, as well as rail-specific objects such as tracks or catenary poles, as training data. However, only very few datasets are publicly available and these available datasets typically involve only a limited number of sensors. Datasets and trained models from other domains, such as automotive, are useful but insufficient for object detection in the railway context. Therefore, this publication presents OSDaR23, a multi-sensor dataset of 21 sequences captured in Hamburg, Germany, in September 2021. The sensor setup consisted of multiple calibrated and synchronized IR/RGB cameras, lidars, a radar, and position and acceleration sensors front-mounted on a railway vehicle. In addition to raw data, the dataset contains 204 091 polyline, polygonal, rectangle and cuboid annotations for 20 different object classes. This dataset can also be used for tasks going beyond collision prediction, which are listed in this paper.**

I. INTRODUCTION

In automatic train operation (ATO), technical systems take over tasks that had previously been performed by the operating staff. ATO includes different grades of automation (GoA), up to GoA4 in which the train is fully automated with no staff on board.

In nowadays operation, one of the main tasks of the train driver is to monitor the train's driveway to predict collisions and act accordingly. The train's driveway is also known as the train's path [1]. This task is rated the most challenging according to a lately conducted rail industry survey [2] and impedes an automation upgrade to GoA3 and GoA4, where no train driver is needed. In this regard, ATO of mainline trains differs from metros. Fully automated metros, such as the Nuremberg U-Bahn, are closed systems meaning that traffic runs in isolated and mostly enclosed environments such as tunnels, and therefore on-board computer vision (CV) systems are not required to replace human vision for driveway monitoring [3]. In contrast, open rail systems are subject to environmental interferences, e.g. at level-crossings or on unfenced tracks. Therefore, various classes of objects may protude in the train's driveway and need to be detected. Hence, replacing human vision with CV systems is a growing area of research for mainline railway.

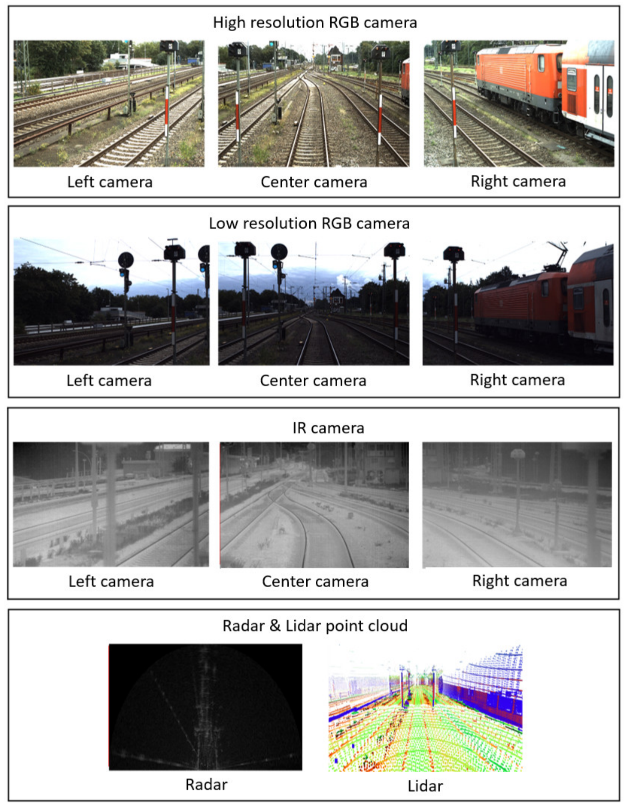

Fig. 1. Captured data in a railway environment.

Developing advanced CV systems for mainline railways requires machine learning [4], and therefore large amounts of sensor data. Currently, only a few datasets with objects from the railway environment are available and these datasets are often limited. In order to narrow this gap, this publication presents the "Open Sensor Data for Rail 2023" (OSDaR23) [5], [6], a freely accessible annotated multi-sensor dataset containing objects that are relevant to CV systems in the context of mainline railway and beyond.

While the development of CV-based collision prediction for ATO is the main purpose of OSDaR23, the dataset may also be used for related tasks and can also serve as a basis for

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extending open datasets created by others. This dataset can enable developers of CV systems to transfer their algorithms to the railway domain, thus fostering research in this area.

OSDaR23 was created in the project “Aufbereitung von Datensätzen für Anwendungen des automatisierten Fahrens im Eisenbahnbetrieb” (English: “Development of Datasets for Applications of Automated Driving in Railway Operations”) conducted by the German Centre for Rail Traffic Research at the Federal Railway Authority (DZSF) using sensor data (cf. Fig. 1) provided by DB Netz AG within the sector initiative of Digitale Schiene Deutschland (DSD). The annotations of this dataset were created by FusionSystems GmbH. The dataset is published together with a research report as well as a labeling guide that specifies how the annotations were created and how future datasets can be annotated similarly. These documents can be obtained from `dzsf.bund.de`.

II. Dataset Requirements for OSDaR23

Fully functional CV systems for collision prediction need to include algorithms for the following three sub tasks: obstacle detection, distance estimation, and track detection [1]. Given these groups, several requirements for datasets for the development of CV systems can be derived.

First, datasets must contain potential obstacles endogenous to the railway system, such as rail cars and buffer stops, as well as exogenous obstacles, such as pedestrians, road cars, animals, trees, rocks, misplaced drag shoes, fires and many others.

Second, objects are only considered to be obstacles when they are in the train’s driveway. While object detection in the railway context usually refers to objects placed on the tracks, obstacles can also belong to rather unusual object types or occur in unusual places as reported cases of bicycles hanging from the catenary illustrate. Therefore, in addition to the existance of objects, their position relative to the drive way needs to be determined. The region of interest (ROI) for object detection includes the tracks as well as the 3D tubular space formed by the predicted train’s driveway and minimum clearance profile. To determine the ROI, the datasets must include tracks and other rail infrastructure objects such as switches and transitions, which allow the prediction of the train’s driveway.

Third, compared to road vehicles, braking distances of rail vehicles are about five times larger, and whistling and emergency braking are the only available reactions to obstacles, since evasion is obviously not an option. Therefore, datasets should include data from sensors that include objects at larger distances over several hundred meters.

Fourth, object detection performance doesn’t only depend on the distance of an object, but also on several other factors, such as the size of the object, the visual contrast of the object compared to the background, the speed of the ego-vehicle, the weather and time of the day, the occlusion of the object by other objects and other visual conditions. As a reference, Tab. I presents median distances for human train driver’s performance in detecting objects, which might serve as a benchmark in safety argumentation [7]. Therefore, another requirement is that datasets need to contain data collected under these different circumstances.

TABLE I
Human detection of objects on railway.

Object (area or size)	Median distance of detection in m
$\geq 0.4\,\mathrm{m}^2$, 30 % (visual) contrast	> 750
$2\,\mathrm{m}^2$, 8 % contrast	500
$0.4\,\mathrm{m}^2$, 8 % contrast	240
$2\,\mathrm{m}^2$, 30 % contrast, at night	180
$0.4\,\mathrm{m}^2$, 30 % contrast, at night	60
$\leq 2\,\mathrm{m}^2$, 8 % contrast, at night [8]	< 60
$40 \times 40 \times 40$ cm	250
$20 \times 20 \times 20$ cm	175
$10 \times 10 \times 10$ cm	50
$5 \times 5 \times 5$ cm	< 25
fluorescent objects at night, 60 km/h [9]	
person in safety jacket	400
passenger car	300
person	240
passenger car at night, person with and without safety jacket at night [10]	< 60
tree, 50-70 km/h	60
fallen rock, 20-120 km/h	30
Japanese accident statistics [11]	

Fifth, depending on GoA and the technical implementation, the task of detecting train signals and their meaning is either conducted by a human, a CV system, or by cab signaling (GoA2). In case of CV systems, the datasets must contain annotated signals. It should also be taken into account that railway signals significantly differ from street signs in shape, colour and placement as well as among railway systems of different countries.

Lastly, it is necessary to predict the future trajectory of objects in order to determine whether a collision is likely to happen or not. This requires tracking objects over time. Therefore, the datasets need to contain tracking identifiers that allow mapping different annotations to the same physical object. Therefore, datasets must contain tracking IDs that allow mapping of different annotations to the same physical object.

III. Existing Datasets for CV in Railway

To the best of the authors’ knowledge, RailSem19 [12], FRSign [13], RAWPED [14] and GERALD [15] are the only CV datasets recorded by frontal on-board sensors of a railway train including object annotations that have explicitly been published for free use by the research community. They contain annotated single RGB-camera frames from video sequences. RailSem19 contains 8 500 frames of railway and tram scenes from 38 countries. It contains annotations in form of geometric shapes and dense pixel-wise semantic segmentation for trains, switches, switch states, platforms, buffer stops, rail traffic signs and railway signals. FRSign is a dataset of 105 352 frames annotated with boxes of French railway signals in different signal states and GERALD a dataset of 5 000 frames containing German signals. RAW-

Fig. 2. The utilized vehicle, with the mounted sensor setup [6].

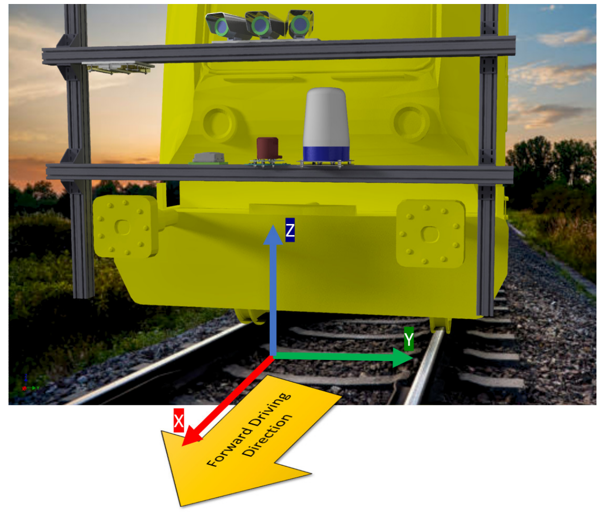

Fig. 3. The utilized reference coordinate system.

PED contains 26 000 frames with box annotations for pedestrians. In addition to open datasets, there are also datasets that have been used in research but have not (yet) been published, such as, the RAILOD dataset of 4 651 manually annotated single RGB-camera frames from 6 scenes [16].

IV. Motivation for OSDaR23

OSDaR23 [5] is a manually annotated open dataset with a multi-sensor setup for the railway environment. The multi-sensor setup includes cameras, lidars, a radar as well as position and acceleration sensors. In contrast, available open datasets for railway focus mainly on camera images. The goal of creating OSDaR23 was to advance the development of AI algorithms for the next GoA of mainline railways, in terms of object detection. Another related goal is making developers of AI systems more familiar with the railway context and to support standardization activities for the safety approval process [17].

V. Multi-Sensor System

OSDaR23 was recorded on several data collection runs in September 2021 in Hamburg, Germany, by DB Netz AG. The dataset contains sensor data collected under regular operating environments and situations. Additionally, some special situations and objects, e.g. flames and smoke, were staged. The vehicle utilized for data collection was a track working vehicle with attached profiles. Fig. 2 shows the sensors at the front of the vehicle mounted on the profiles. The sensor configuration included a total of six RGB cameras, three IR cameras, six lidar sensors with different ranges and field of view (FoV) coverage, a 2D radar sensor, and position and acceleration sensors (GNSS+IMU). The camera, lidar, and radar data are shown in Fig. 1. The main technical specifications of the sensors are listed in Tab. II. The sensors were calibrated according to the reference coordinate system shown in Fig. 3. The FoV areas of the sensors covered the area in front and partially to the side of the vehicle and overlap each other.

The sensors were synchronized at a frame rate of 10 Hz based on the acquisition time of each sensor. The sensors used the Precision Time Protocol (PTP) in order to synchronize their clocks. As the radar has a capturing rate of 4 Hz only, some radar images are duplicated. The union of frames from all sensors at a given point in time forms a multi-sensor frame (m-frame). For the dataset, the point clouds of the six lidars were ego-motion compensated and merged into a single point cloud per m-frame.

VI. Annotation Specification

In addition to the raw sensor data, the annotations are the core part of OSDaR23. A labeling guide forms the basis for the manual creation of annotations by the annotators. The annotation guide in this project refers to the described sensor data from IR/RGB cameras, the radar and point cloud data from the lidars. In the camera and radar frames, axis-parallel and rotated rectangles, polylines and polygons are used as two-dimensional (2D) annotation geometries. The rectangles and polygons enclose the annotated objects in the sensor images as accurately as possible. The polylines are used to annotate tracks and transitions – they follow the outer rail edges. In the lidar point clouds, three-dimensional (3D) cuboids and polylines are used, as well as semantic segmentations. Cuboids enclose objects and polylines mark contours analogous to the 2D annotations. In semantic segmentations, individual lidar points are assigned to an object.

Using these geometries, objects of 22 different classes from four different categories were annotated. The classes for dynamic objects are person, crowd, train, wagons, bicycle, group of bicycles, motorcycle, road vehicle, animal, group of animals, wheelchair, and drag shoe. The railway related objects are track, switch, and transition. Static objects are catenary pole, signal pole, signal, signal bridge, and buffer stop. Special classes are flame and smoke. As the sensor data were recorded in Germany, only German railway signals are part of the data set. All object annotations have tracking IDs by which they can be assigned to the same physical object in the real world in all m-frames of a sequence.

TABLE II

MULTI-SENSOR SYSTEM

Three 12MP RGB cameras	
Type	Teledyne GenieNano 5GigE C4040
Sensor data	RGB images (8 Bit, PNG)
Resolution	$4\,112 \times 2\,504$ px
Sampling frequency	10 Hz (synchronized)
Alignment	trident (in driving direction diagonal left, central and diagonal right)
Three 5MP RGB cameras	
Type	Teledyne GenieNano C2420
Sensor data	RGB images (8 Bit, PNG)
Resolution	$2\,464 \times 1\,600$ px
Sampling frequency	10 Hz (synchronized)
Alignment	trident
Three IR cameras	
Type	Teledyne Calibir DXM640
Sensor data	grayscale images (8 Bit, PNG)
Resolution	640×480 px
Sampling frequency	10 Hz (synchronized)
Alignment	trident
Three long-range lidars	
Type	Livox Tele-15
Sensor data	3D point cloud (PCD)
Total sampling points	50 000 - 84 000 points per frame
Sampling frequency	10 Hz (synchronized)
One medium-range lidar	
Type	HesaiTech Pandar64
Sensor data	3D point cloud (PCD)
Total sampling points	60 000 - 115 200 points per frame
Sampling frequency	10 Hz (synchronized)
Two short-range lidars	
Type	Waymo Honeycomb
Sensor data	3D point cloud (PCD)
Total sampling points	20 000 - 40 000 points per frame
Sampling frequency	10 Hz (synchronized)
One radar	
Type	Navtech CIR204/H
Sensor data	grayscale images (8 bit, PNG), cartesian bird's eye view
Resolution	$2\,856 \times 1\,428$ px
Sampling frequency	4 Hz (synchronized)
Global navigation satellite system (GNSS) sensor with inertial measurement unit (IMU)	
Type	NovAtel PwrPAk7D-E1
Sensor data GNSS	latitude and longitude in WGS84
Sensor data IMU	linear and rotatory acceleration
Sampling frequency	100/10 Hz

The annotations are provided in JSON-files that follow the RailLABEL JSON schema. The RailLABEL schema is a sub-schema of the ASAM OpenLABEL standard [18] developed by the Association for Standardization of Automation and Measuring Systems (ASAM). The development kit for this dataset is online available on `github.com/DSD-DBS/raillabel`.

Details on class attributes, annotation rules and the storage format are presented in the project report and in the separately published labeling guide [17]. Fig. 4 shows two examples for the sensor data and its associated annotations. In the left column a recording of the main station in Hamburg is presented. In the right column a capture closed to station Hamburg-Ohlsdorf is shown. The first row shows the images from the center camera. In the second row the ego-motion compensated and merged point clouds of the lidars are shown. The third row presents the data of the central IR camera. In the last row the outcome of the radar is pictured. Please note, that the radar images are zoomed in due to the long viewing range of the radar.

TABLE III

NUMBER OF ANNOTATIONS PER OBJECT CLASS

Object Class	Count	Object Class	Count
person	73 421	bicycle	1 779
signal	32 790	crowd	1 352
catenary pole	27 706	bicycles	644
track	18 543	transition	636
signal pole	14 374	flame	410
road vehicle	12 669	signal bridge	312
train	8 290	smoke	188
buffer stop	4 539	wagons	110
animal	3 288	drag shoe	79
switch	2 947	motorcycle	14

VII. OSDaR23 Statistics

The annotated dataset comprises 21 sequences, divided into 45 subsequences, with a total of $1\,534$ annotated m-frames and $204\,091$ annotation objects. Since an m-frame is composed of nine camera frames, one radar frame and one lidar frame, the total number of individual sensor frames is $1\,534 \cdot 11 = 16\,874$. An annotation object refers to the annotation of a physical real-world object captured in a sensor at a point in time. A real-world object is typically captured by multiple sensors and over multiple points in time and is therefore represented in multiple annotation objects. To cover a wide variety of object classes and environments while enabling the development of object tracking, the dataset contains several shorter sequences of different locations and situations with ten m-frames each as well as some longer sequences of 40 to 100 m-frames. The most common annotation objects are persons such as passengers or staff. These are followed by static objects such as signals, catenary poles, tracks, signal poles, buffer stops, and dynamic objects such as road vehicles and trains. Tab. III gives an overview of the distribution of the annotation objects.

VIII. Limitations

First, OSDaR23 does not provide an associated digital map. However, a digital map can be created from the annotated data using visual odometry or self-localization.

The annotation of signals does not include the association with the belonging tracks. Since exceptions to the rules for signal placement exist, these associations can not be easily derived [19]. Furthermore, OSDaR23 does not provide the classification of signal states.

Automation of shunting operation in shunting yards without signaling requires recordings and annotations of fouling point indicators at the railway switches, which OSDaR23 does not provide.

The visual inspection of the infrastructure and vehicle is an important task to prevent accidents additionally to predictive maintenance. Sun kinks, rail breaks, gravel underwashing floods, catenary damage, broken signals, dysfunctional level-crossing gates and slipping load of crossing trains must be

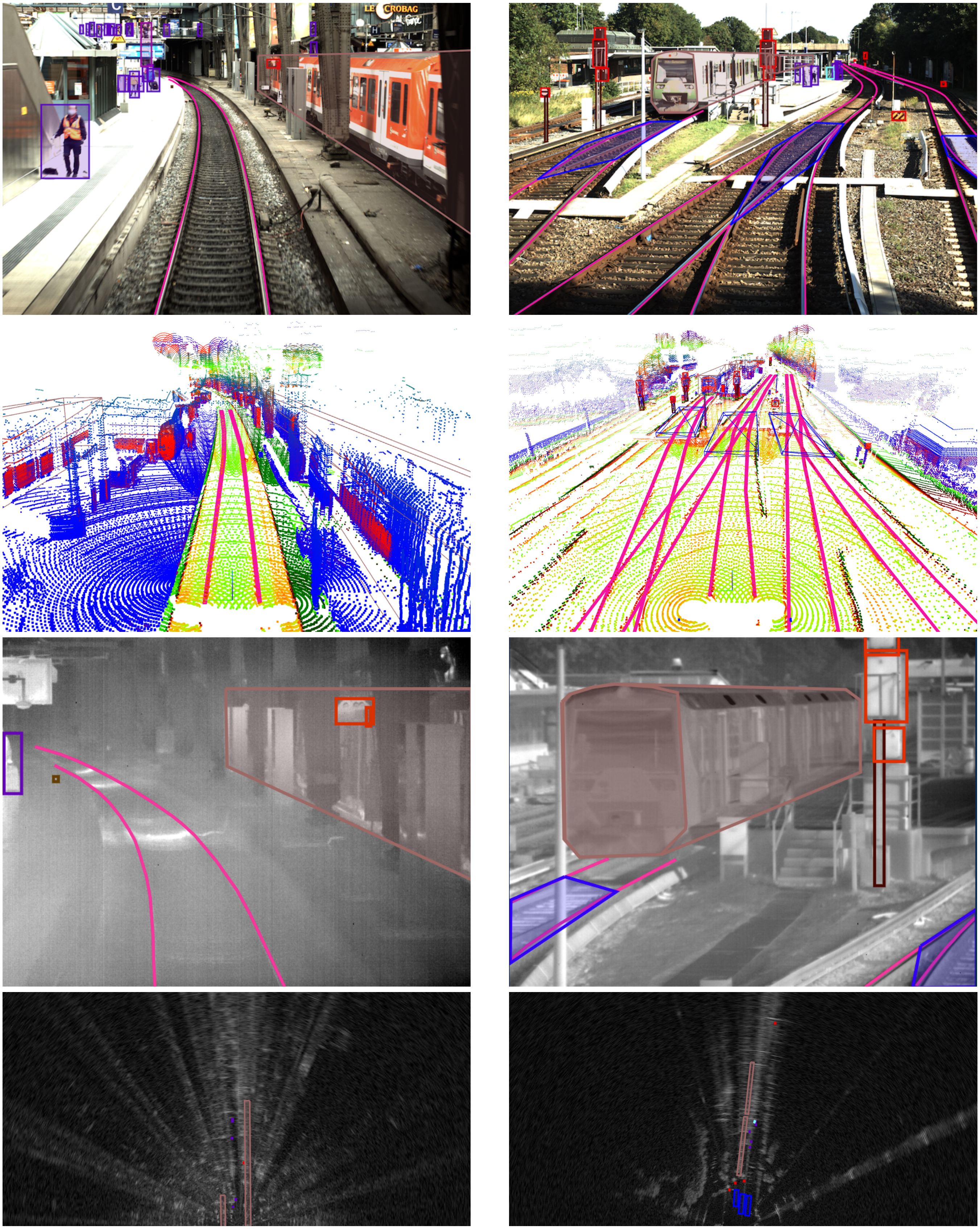

Fig. 4. Examples for annotated sensor data from OSDaR23. Left column: Sequence inside Hamburg Main Station. Right column: Sequence at Station Ohlsdorf. First Row: RGB center camera. Second Row: Merged Lidar point cloud. Third row: IR center camera. Last Row: Radar (zoomed).

detected to induce emergency braking. However, such cases are not covered by OSDaR23.

IX. Conclusion and Future Work

In this article, the multi-sensor dataset OSDaR23 [5] for the railway environment is presented. The sensor setup consists of multiple calibrated and synchronized IR/RGB cameras, lidars, a radar as well as GNSS+IMU sensors. During data collection, the sensors were mounted on the front of a track work vehicle. The dataset contains 204 091 annotations for 20 different object classes from total 22 defined in the labeling guide. Therefore, OSDaR23 can be used for the development of AI models for collision prediction and object detection required for ATO. The dataset can be extended with user-specific complementary data like objects intruding into the railways.

Today, there are more than 200 known methods for pedestrian motion prediction [20], which can be tested on OSDaR23. Detecting pedestrians is a very important task as trespassing railways is a life-threatening criminal offense that also obstructs train operation.

Further datasets beyond OSDaR23 will be required to develop CV systems fulfilling high safety requirements of ATO. They should include different sensor configurations, a quantitative increase of data, qualitative expansion of the object classes, their attributes, geometries, environments, and situations as well as recordings of unusual, (anticipated) critical and incident events.

OSDaR23 will be integrated in the DSD Data-Factory [21]. The Data-Factory is a platform for the systematic provision and processing of sensor data for the development of AI functions and for the simulation of photorealistic scenarios including reasonable trajectories of the relevant objects as well as artificial sensor data.

The DZSF continues the activities in processing and publishing sensor data with the support of DB Netz AG.

OSDaR23 and its annotation specification can serve as a reference as well as a basis for extensions, which will fill the gaps described in Sec. VIII. Developers of CV systems that work in related fields of research like visual infrastructure inspection [22], automated security surveillance [23], train door operation, digital railway mapping etc. performed on-board and off-board might take advantage of these extensions and contribute to the development of further datasets. All stakeholders in the rail sector and beyond are invited to participate in this effort and, if possible, publicate new datasets to achieve a broad research and development community.

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