Performance Metric for Horn and Brake Automation on Mainline Trains

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Abstract: This paper argues for the introduction of a mainline rail oriented end-user performance metric for driver-replacing on-board perception systems. Perception at the head of a train is analysed and divided into several subfunctions. This paper presents a preliminary submetric for the obstacle detection subfunction, focusing on false-negatives. To the best of the authors' knowledge, there is no other such proposal for rail on-board perception systems. A set of submetrics for the subfunctions should facilitate the end-user oriented comparison of perception systems and guide the measurement of human driver performance. It should also be useful for a standardised predictive assessment of the number of accidents for a given perception system in a given operational design domain. In particular, for the proposal of the obstacle detection submetric, practitioners among the readership are invited to provide their feedback and quantitative information to the authors. In addition to the interim feedback, the analysis results of the full feedback will be published later.

1 INTRODUCTION

Driverless and unattended train operation (DTO and UTO) have several advantages (Singh et al., 2021), including increased capacity, reliability, service flexibility, energy efficiency, and alleviation of driver shortages. So far, these advantages can only be realised in the case of metros and other trains without significant exogenous influences. "AutoHaul" (Yusuf et al., 2020) is the only known mainline rail system to implement UTO. It is a heavy-haul train that operates regularly in a sparsely populated area and relies solely on collision detection rather than contactless automatic perception. DTO for mainline trains is still an unresolved challenge in most cases. The crucial difference is that on most mainline tracks the exogenous influences are significant and large scale fencing or walling is usually not economically justifiable and has not been proven to be sufficiently effective.

Mainline rail automation is related to road traffic automation and can benefit from technology transfer. It requires the development of an on-board AI system cabable of multi-sensory perception. However, a literature review showed an order of magnitude lower research activity for rail than for road (Tagiew et al., 2023). It also showed insufficient progress – the current technology readiness level (TRL) for on-board collision prediction is 5 and has not been exceeded for two decades. A key finding was the lack of a widely accepted end-user performance metric that could link rail safety requirements with the perception system development community.

This paper addresses the lack of an end-user performance metric for rail on-board AI perception systems. Such a performance metric would, on the one hand, provide developers with clear application-oriented goals, make their results comparable and, on the other hand, make progress measurable for outsiders. The paper proposes a preliminary performance submetric for the major subfunction of obstacle detection, which primarily improves measurement of false-negative detection of obstacles. Based on this proposal, a discussion can be started and first performance results of perception systems can be compared. Practising readers of this paper are encouraged to actively submit either the performance data of their systems or their suggestions for improving the performance submetric to the author by any appropriate means. In addition, this paper introduces the state of the art to developers unfamiliar with railways, in order to facilitate the research.

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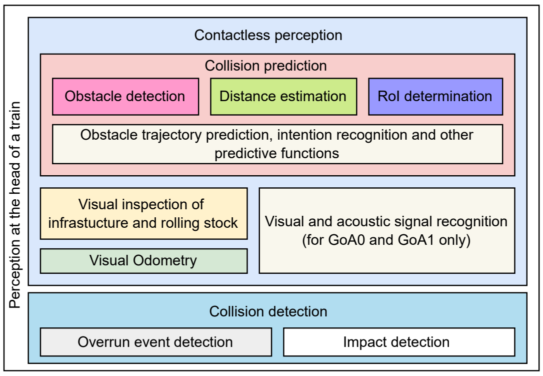


Figure 1: Rough categorization of system's functions for mainline DTO, which in comparison to DTO of metros, require additional technological effort (Tagiew et al., 2023).

2 SUBFUNCTIONS

AI perception systems that replace human staff on mainline trains need to perform multiple functions. Considering the current state of the art, these functions will not represent the full range of human capabilities one-to-one, but only cover the most relevant functions with at least the same or higher level of performance. Non-implemented functions might be compensated by higher performance of the implemented functions. For example, infrared sensors for better night vision could compensate for poorer intention recognition of humans. The functions can be divided into two main sub-functions, the perception of objects with and without physical contact (fig.1). Fig.1 does not include many subfunctions, such as door operation monitoring, emergency detection, crime detection, etc.

Perception by contact with objects is referred to here as collision detection and replaces the train driver's acoustic and haptic sensation. Already in EN 62267, a standard for driverless metros, it is mentioned that a collision has to be detected at the latest at the contact with an obstacle. In the special case of shunting, controlled collisions such as running into a drag shoe or coupling of cars are part of normal operation. In all other cases, collisions with objects are unwanted, dangerous accidents that cannot always be avoided and must always be detected. Two types of collisions can be identified so far, impact and overrun events. The detection of impact events is referred to here as impact detection. For mainline railways, little research on impact detection and only one seminal research on overrun event detection systems (Herrmann et al., 2023) are known. Collision detection is therefore at a very early stage of development.

Contactless obstacle detection replaces human vision from the cab. It encompasses several tasks, of which collision prediction is the most challenging (Leinhos et al., 2022). It is assumed that collision prediction is always prone to errors, false negatives and false positives, and therefore cannot make collision detection obsolete.

Visual inspection of infrastructure and rolling stock is more important for mainline railways than for metros due to greater exogenous influences and larger operating areas, and is not only important for predictive maintenance. There are also cases such as sun kinks, catenary damage, broken signals, malfunctioning railway crossing gates and slipping loads during train meets that require emergency braking and are therefore part of the driving function. Visual odometry complements rotary encoders, inertial measurement units (IMU) and sensors for global navigation satellite system (GNSS).

Railway signals can be recognised from the vehicle as if it were a human driver. There are several groups of signals, which can be visual or audible. In case of shunting for the lowest grade of automation (GoA) 0, signals are e.g. fouling point indicators at the railway switches. Although the detection of signals is ensured by automatic train stop in case of GoA1, they still have to be recognised from the vehicle. The challenge of signal detection also includes detection of tracks and their assignment to the signals (Petrović et al., 2022; Staino et al., 2022). From GoA2 on, most visual signals do not need to be detected and are transmitted by cab signalling when used with ETCS. The GoA2 is also conceptually feasible if an automatic visual detection of signals assists the driver (Hofmann et al., 2023).

Prediction of collision with obstacles requires algorithms for obstacle detection, distance estimation, region of interest (RoI) determination, obstacle trajectory prediction, pedestrian intention recognition and other predictive functions. Depending on the choice of the operational design domain (ODD), some of the functions, such as pedestrian intention recognition, may be unnecessary. Obstacle detection can be further divided into object detection, obstacle classification and spatial angle determination. There are internal obstacles such as rail vehicles and buffer stops. The external obstacles can be people, road cars, large animals, trees, rocks, wrongly placed drag shoes, floods, fires and similar. Obstacles do not only appear on the ground, they might also hang on the catenary or levitate in the air. For example, bicycles might hang on the catenary (Augsburger Allgemeine, 2014; Oberhessische Presse, 2015; STIMME, 2021; RUHR24, 2022; Fränkische Landeszeitung, 2022).

Distance estimation is important for shunting and

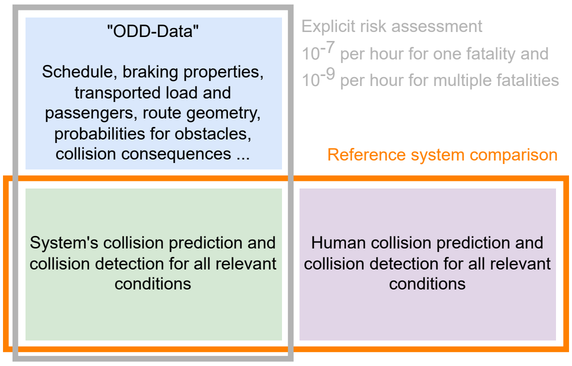


Figure 2: Data required for two currently available approaches of safety argumentation for European mainline railway systems (Tagiew et al., 2022). The grey frame denotes the explicit risk assessment with resulting hourly fatality rates and the maximal values of harmonized design goals. The orange frame denotes the comparison with the a human train driver as reference system.

also for detecting obstacles from long distances in curves, where a relatively small distance error determines whether or not an object intersects with the structure gauge (Gebauer et al., 2012). Spatial angle determination together with distance estimation is referred to as obstacle localisation.

For the RoI determination, a 3D tubular space formed by the predicted train's driveway and the structure gauge should be determined in the scene. Train's driveway is also known as train's path (Ristić-Durrant et al., 2021). The structure gauge is supplemented with a speed-dependent hazard zone for people, which arises due to wind drag of the train (GUV-R 2150, 2008). In the rare case that the states of the switches are not otherwise available to the perception system, they must be extracted from the visual input for the train's path prediction.

3 SAFETY ARGUMENTATION

All subfunctions, described in Sec.2, require performance-indicating submetrics for all relevant stakeholders, especially the developers and the regulators. Safety relevant functions for European mainline railways are approved according to the EU Regulation No. 402/2013 (CSM-RA) (European Union, 2013). Herein, performance metrics are needed, which allow proof of compliance with standards, comparison with human performance or calculation of resulting hourly fatality rates. Since there are still no standards for this, only two remaining approaches of safety argumentation are available (fig.2). These are the reference system comparison and explicit risk assessment according to harmonised design goals.

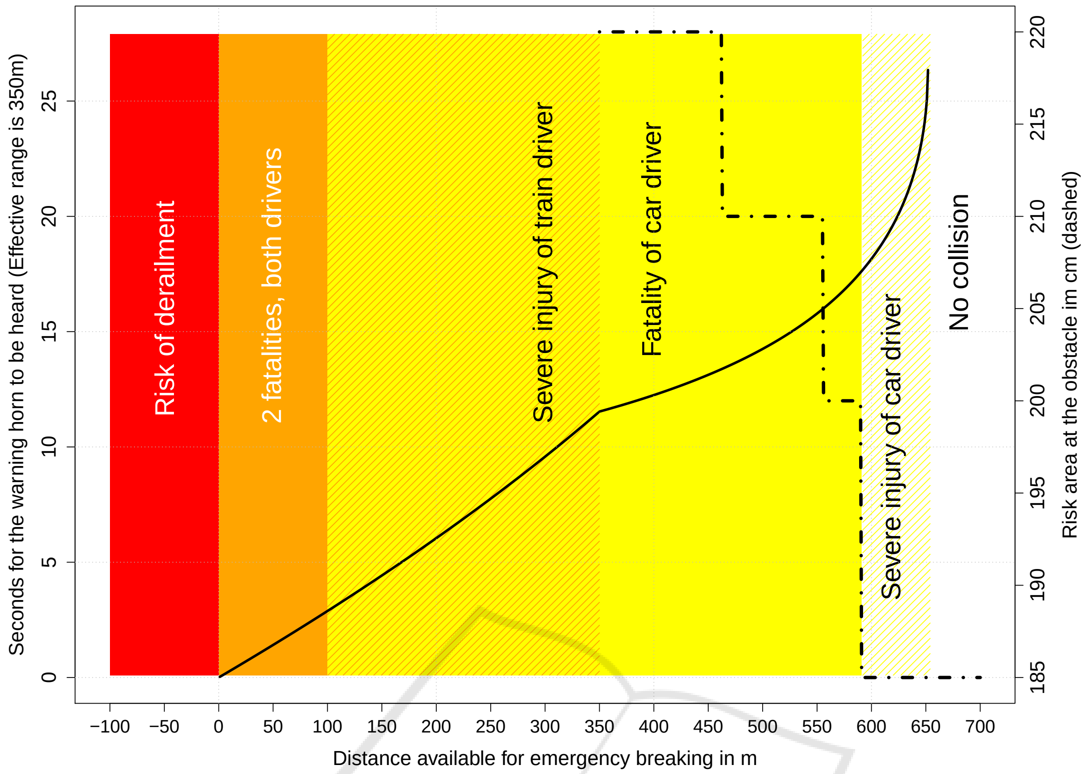
As depicted in fig.2 for collision risks, both approaches need performance data of the system's collision prediction and collision detection for all relevant conditions. Explicit risk assessment requires additional data to calculate, whether the probability of an accident with a single fatality is lower than 10^{-7} and for an accident with more than one fatality is lower than 10^{-9}. This additional data includes schedule, braking properties, route geometry, probabilities for obstacles, collision consequences, acoustic properties for warning horn, transported load and passengers. This data describes the ODD of a train and is called here ”ODD-Data”. Instead of ODD-Data, the reference system comparison needs performance data of human collision prediction and collision detection for all relevant conditions.

4 OBSTACLE DETECTION

To justify performance metrics, this section provides a detailed analysis of obstacle detection in the railway domain with a focus on safety. Commonly used performance metrics for image processing do not correlate well with the safety argumentation. Reference system comparison requires metrics applicable for both humans and machine. Explicit risk assessment requires domain-specific redesign and adjustment of the metrics. In particular, the performance metric intersection over union (IoU), which is oriented to the 2D space of camera images, could mislead the development of a perception system. Even in 3D space, IoU still requires a safety-oriented weighting of the spatial direction of the mismatch between prediction and ground truth. Mean average precision (mAP) based on IoU provides a value only for single shot prediction, not for a sequence of images of a train approaching an obstacle.

According to Eurostat statistics for 2021 in the EU (EUROSTAT, 2022), 64.5 % of fatalities result from accidents to persons by rolling stock in motion, 34.3 % from level crossing accidents including pedestrians and only 1.2 % from railway vehicle collisions and other accidents. The portion of pedestrians in level crossing accidents can be assumed to be 14.6 % based on German statistics by Deutsche Bahn (Deutsche Bahn, 2019) for 2018. Therefore, the most probable fatal type of an accident is collision with a person at roughly 70 %. Second most probable accident type is collision with a road car at roughly 24 %.

The circumstances that can lead to accidents are also known as critical scenarios according to ISO 34502 (ISO 34502, 2022) and hazardous situations according to IEC 62267 (IEC 62267, 2009) and ISO



$$t = \frac{1}{a}\left(\left(\begin{cases} v & 0\,\mathrm{m} \le d < 350\,\mathrm{m} \\ \sqrt{v^2 - 2a(d - 350\,\mathrm{m})} & 350\,\mathrm{m} \le d \le 652\,\mathrm{m} \end{cases}\right) - \sqrt{v^2 - 2ad}\right)$$

Figure 3: Estimated consequences for a frontal collision of a train going at 130 $^{km}/_{h}$ with a stationary passenger car depending on braking distance (Tagiew et al., 2022). The braking deceleration is set to be 1 $^{m}/_{s^2}$. The driver can hear the warning horn at a distance of 350 m or less and may be able to escape. Negative distances mean the onward movement of an unbraked collided train. Warning horn and emergency braking start simultaneously. The solid kinked curve shows the number of seconds between hearing the warning horn by the car driver and the collision. The formula for this curve is added below the graph and provides an explanation for the kink (t-time, a-decceleration, v-speed, d-distance). The dashed zigzag line depicts the size of the risk area at the collision site. For the sake of simplicity, it is assumed in this that the derailment risk in this example is only present in collisions at speeds of 130 $^{km}/_{h}$ and above.

22737 (ISO 22737, 2021). For the sake of simplicity, the term scenario is used to refer to these in this paper.

Both the most common scenarios on railways, pedestrian and car collisions, are also the most common on roads (BASt, 2023). Unlike road vehicles, emergency braking and warning horn are the only reactions available on rail vehicles. The braking distance for rail vehicles is approximately 5 times longer than for road vehicles. The $\approx$ 15 dB(A) louder warning horn can and should be heard from larger distances (StVZO, 2016; Schöne and Bagola, 2013). This changes the minimum acceptable performance of collision prediction and requires long range object detection (LROD). Due to curves, weather and light conditions, LROD is not always possible. Whereas for road vehicles, collision prediction enables collisions to be mostly avoided, for rail vehicles it is more a matter of damage limitation and deference.

Collision with a person causes a fatality for all ego vehicle speeds in case of railways as according to DIN VDE V 0831-103. However, out of a total of 695 accidental fatalities and serious injuries in 2021 in EU caused by rolling stock in motion, 36.5 % were seriously injured, i.e. survived (EUROSTAT, 2022). When a deadly collision with a person cannot be prevented, the braking must be applied to preserve the dignity of the dead, to facilitate investigation by authorities and prevent exposure to casual bystanders. This is also important for the more than 2 000 rail suicides in EU each year, which are not counted as accidents. Warning horn and braking is never too late and has to be done as soon as possible in this scenario.

Table 1: Human detection of objects on railways in *m*.

Object	Median distance of detection
fluorescent objects at night, 60 km/h, measurements/simulation (Itoh et al., 2001)	
$40 \times 40 \times 40$ cm	250
$20 \times 20 \times 20$ cm	175
$10 \times 10 \times 10$ cm	50
$5 \times 5 \times 5$ cm	< 25
measurements (Polz et al., 2003)	
$0.4\,m^2$ & $2\,m^2$, 30 % contrast	> 750
$2\,m^2$, 8 % contrast	500
$0.4\,m^2$, 8 % contrast	240
$2\,m^2$, 30 % contrast, night	180
$0.4\,m^2$, 30 % contrast, night	60
$0.4\,m^2$ & $2\,m^2$, 8 % contrast, night	< 60
measurements (Mockel et al., 2003)	
person in safety jacket	400
passenger car	300
person	240
passenger car, night	< 60
person in safety jacket, night	< 60
person, night	< 60
statistics of accidents (Nakasone et al., 2017)	
trees, 50-70 km/h	60
fallen rocks, 20-120 km/h	30

Collision with a passenger car is more intricate scenario than with a person regarding the consequences of different ego vehicle speeds. Fig.3 shows the roughly estimated consequences for the collision of a train travelling at 130 km/h with a stranded passenger car. For simplicity, a uniform emergency braking deceleration of 1 m/s² without delay is assumed. More realistic modeling would require consideration of additional modifiers such as co-functioning of different types of brakes, sanding to improve adhesion, and surge behavior of the liquid load. In the best case, if the car is recognised at more than 652 m, the emergency braking can prevent the collision. In the worst case, if the car is not recognised before the collision, the impact detection system should recognise the crash and break to reduce the risk of a potential derailment of the train. The LROD can not always achieve the best case due to obstruction of view in curves, through hilltop, weather conditions, insufficient illumination, as well as due to sudden intrusion of a moving obstacle.

However, earlier braking between the best and worst case reduces harm, which can be shown in our example in fig.3. According to the risk model by ENOTRAC (Moser and Schibig, 2017), the damage of obstacles to a train grows with their mass and the speed of the train. According to DIN VDE V 0831-103, a crashing train with a speed higher than 40 km/h will cause fatality of the car driver. If the car driver can escape the car after hearing the warning horn, early braking gives more time for the resort depicted as solid curve. The assumption for the maximal distance of 350 m at which the warning horn can be heard by the car driver is derived from the German regulation for the maximal distance between a railway crossing and a whistle board (Volker Behrendt, 2012). A lower speed at the obstacle as a consequence of early braking reduces the risk area created by air stream around the vehicle depicted as dashed zigzag line as according to the speed thresholds in the regulation of German Statutory Accident Insurance (GUV-R 2150, 2008).

The distribution of distances, at which human drivers detect objects on railway, has an irregular bell shape (Tagiew et al., 2022). Tab.1 shows median distances for human performance at detecting objects on the tracks from all known sources. According to these measurements, a human driver can prevent collision with the car only if the car is of contrasting paint and is presented at daylight. At night without illumination, rainy weather and a decent car paint, the consequences will be much more severe. The shapes of the obstacle detection distances distribution are much steeper for computer vision systems than for humans (Mockel et al., 2003; Nakasone et al., 2017). One source reports distances (Zhangyu et al., 2021), at which first more or less erroneously placed boxes appear for target objects.

False-negative and false-positive obstacle detection may occur due to reproducible or irreproducible failures in sensors and algorithms. The failures can be assigned to certain functions in certain cases. For example, objects such as stones and trees from the perceived space outside of RoI may be detected as obstacles due to wrong localisation of them or to wrong localisation of RoI. The space perceived by sensors is often larger than the 3D RoI, even in the presence of view obstructions. Another example is small animals that are recognised as obstacles because they are misclassified as humans or vice versa. Computationally, moreover, false-positive visual detection, i.e., false alarms, must occur much less frequently than false-negatives, since the case of absent obstacle is overwhelmingly predominant and obstacles are extremely rare. Additionally, mainline rail vehicles' emergency brakes can not be interrupted until full stop in many cases, obstruct the railway operation, damage to the vehicles and constitute therefore a significant cost factor, which has to be considered in the performance metrics. Since false-positive detection can not be out-

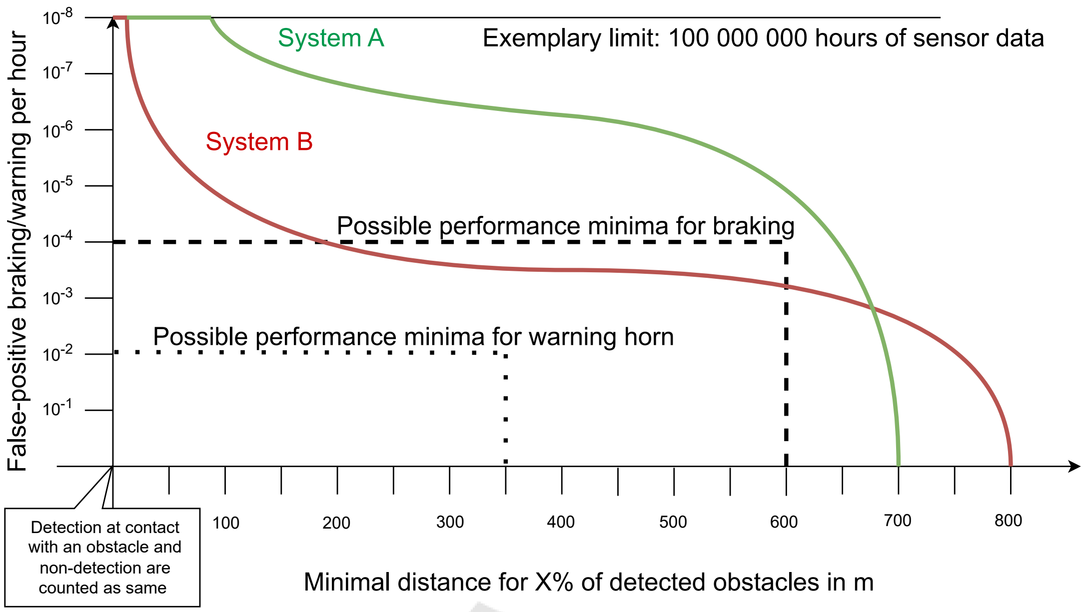


Figure 4: Performance submetric for obstacle detection with results of two hypothetical systems A and B. X can be replaced by a positive number up to 100. A detection on contact with an obstacle and a non-detection are counted as the same.

ruled, collision prediction will be most probably complemented by collision detection to refute false visual detection (Tagiew et al., 2022).

5 PERFORMANCE SUBMETRIC

Fig.4 shows the proposed obstacle detection end-user metric. This metric is designed for moving train. The abscissa shows the distances, at which $X\%$ of appearing obstacles are detected while approaching them. $(100-X)\%$ are detected at closer distances. Setting $X = 50$ would denote a median distance for obstacle detection. The ordinate shows hourly rates of false-positive detections, which will cause unneeded warning horn and jam-creating emergency braking. The values on the ordinate are negative logarithms of the hourly rate, the lower the better. The performance values of a system on these two axes are interlinked and can be adjusted by changing detection thresholds and tweaking internal parameters of a system. Like with precision-recall (PR) and receiver operating characteristic (ROC) curves, increasing performance on the one axis will most probably reduce performance on the other axis.

The results according to this metric depend on the number and type of obstacles, the speed of the ego vehicle, the frame rate of the sensors, the track geometry, the time of day, the weather conditions, and other properties of a data set used to validate a system. The characteristics of the validation dataset will most likely depend on a chosen ODD. The shape of such performance curves is speculative and is shown in Fig.4 for hypothetical systems A and B.

Both systems A and B have maximum ranges due to their sensor resolutions. The measurement errors of currently used sensors such as Lidar, RGB/IR camera and Radar increase over longer distances (Leinhos et al., 2022). Weather and light conditions can exacerbate this effect. Robust object detection using deep neural networks requires a minimum number of pixels. Setting the internal thresholds of one system to the extreme of permanent positive detection will give the maximum range on the abscissa and 10^0 on the ordinate. The opposite extreme, where the system is in permanent negative detection, will result in 0 on the abscissa and 10^{-H} on the ordinate. 10^{-H} is the number of hours of sensor data available for evaluation and is set to 100 million as an example. The shapes of the curves in between for the hypothetical systems are drawn based on intuition. From the shape of the curve for the system A, it can be inferred that $(100-X)\%$ of car-collision scenarios will result in one or more fatalities with this system adjusted to $< 10^{-4}$ false-positives (fig.3). The system B has to be adjusted to $< 10^{-3}$ false-positives, 10x more inappropriate stops, to achieve the same level of safety.

Based on a certain ODD, there will be certain performance minima for each of the axis. If the functions of emergency braking and warning horn are separated, the performance minima for both functions can be different. In project KOMPAS, 10^{-4} or less false-positive emergency braking per hour is suggested as the minimal acceptable performance (Polz et al., 2003). Since false-positive warning horn does not create jams on the railways, the minimal requirements can be much less rigorous. However, extensive false-positive warning horn will probably not be welcomed by residents living close to the railway. For orientation, this paper proposes a rate of 10^{-2} cases per hour as depicted in fig.4.

The issue with the minima for distances depends stronger on ODD. Certain ego vehicle speeds, driveway geometries, weather and illumination conditions either prohibit or do not demand LROD for safety argumentation. For example in case of car-collision scenario, warning horn is assumed to be effective a most 350 m only. Low ego vehicle speeds or better brakes result in lower distance requirements for obstacle detection. If a typical curved route does not allow sensors to penetrate further forward than 600 m, a system will not be required to have a higher range. Both minima are depicted in fig.4.

In the pedestrian-collision scenario, the emergency braking function demands a system to overcome simultaneously higher minima on both axes than the warning horn function. In such case, system A is better than system B for both functions. For the pedestrian-collision scenario, effective distance for warning horn can be significantly longer than braking way (Schöne and Bagola, 2013; Toward et al., 2022) and that can make system B more appropriate for warning horn subfunction, while system A is more appropriate for emergency braking subfunction.

Once the performance minima are met, the order of preference for both performance values becomes important in the choice of system and system parameter configuration. This could lead to answers to questions such as how much resident annoying extra warning horn is justified to save the life of one unlawful trespasser or one wild animal.

6 ONGOING CALL FOR DATA

The contents of this paper are recently uploaded as preprint to elicit feedback from the research community. It contains a proposal for a submetric for an autonomous train perception system and a rationale for its design. The amount of feedback will be maximized by wide dissemination. The data expected here are lists of measurements that fit within the proposed submetric in fig.4 and 4-tuples of the performance minima for braking and warning. An element in the list of measurement contains the name of the system, the X, rate of false-positives per hour and the minimal distance for $X\%$ detections. Textual feedback is also welcome, especially as reasoning for the suggested performance minima. Also, human performance measurements as benchmark are welcome. The anonymized data from the feedback will be analyzed and published in a separate paper, for which this paper serves as a draft.

Table 2: Survey results for acceptable false-positive brakes.

Per operational hour	Expert votes	%
1 in 100	2	13,33
1 in 1 000	3	20
1 in 10 000	5	33,33
1 in 100 000	3	20
1 in 1 000 000	2	13,33

The interim results of the call for performance data show that at least one development team has a triple digit number of hours of multi-sensor data. Less data is reported to be annotated. The first annotated multi-sensor open dataset OSDaR23 contains only about 3 min of sensor data (Tilly et al., 2023). A survey of 15 experts from German mobility sector conducted during the "Verkehrs- und Infrastrukturtagung (VIT) 2023" in Berlin shows support for the maximal 10^{-4} false positive brakes per hour (Tab.2).

7 CONCLUSION

A very important idea take away is the inaptitude of the concept of a binary false negative rate for obstacle detection for mainline railways. The non-detection of obstacles is gradual and not binary. The question is not "What share of the obstacles is detected?". The question is "At what distance will $X\%$ of the obstacles be detected at the latest?". The other important idea is that smooth operation, or minimising the number of false-positive stops, is the primary goal and more computationally demanding, while safety, or maximising the timeliness of obstacle detection, is the secondary goal.

The main result of this work is the proposal of an end-user performance submetric for obstacle detection by a moving train, based on the two ideas introduced. On the one hand, this submetric should help to correlate the performance requirements of the end-user with the goals of the developers. On the other hand, this submetric makes the train-side perception system comparable and the progress of the perception system measurable for external analysis. A first feedback from mobility experts is already included in this paper. However, the proposal needs more attention from the community of mobility experts for further development and refinement. Another useful outcome is a short introduction to the DTO for mainline rail.

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