Detecting Hazardous Events: A Framework for Automated Vehicle Safety Systems

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Abstract— The driving domain is inherently dangerous. To develop connected and automated vehicles that can detect potential sources of harm, we must clearly define these hazardous events and metrics to detect them. The majority of driving scenarios we face do not materialise harm, but we often face potentially hazardous near-miss scenarios. Potential harm is difficult to quantify when harm is not materialised; thus, few metrics detect these scenarios in the absence of collision and even fewer datasets label non-collision-based hazardous events. This study focuses on detecting near-miss scenarios due to other actors since human error is the primary source of harm. We first provide a concise overview of current event-specific metrics. We then propose an event-agnostic detection framework that exploits vehicle kinematics to detect evasive manoeuvres early and dynamically calculate minimum safe distances. Given inconsistent dataset labelling methods and collision-focused events, we provide a preliminary study to demonstrate an event-agnostic and configurable dataset annotation technique to label hazardous events, even when harm is not materialised. We show promising results detecting hazardous scenes on a labelled simulation benchmark, GTACrash.

I. INTRODUCTION

Road transportation has become ubiquitous in our everyday lives, and the development of connected and automated vehicles (CAVs) aim to automate specific driving functions and improve safety. However, there are many dangers to navigate and with 1.35 M global road traffic-related fatalities per year [1], CAVs must be able to identify hazardous events.

In this research, we focus on hazardous events external to the system and follow the definitions found in ISO 26262 [2] and 21448 [3] for the functional safety of road vehicles and safety of intended functionality, respectively. Factors that pose a "potential source of harm" are defined as hazards [2], [3] and harm can be a physical injury or property damage. Furthermore, the focus of hazard detection is not only on collision events but also on the preceding triggering events that lead up to harm. Nevertheless, the definition of triggering events remains under-explored and unclear in the literature since near-miss scenarios are hard to quantify, although more common in real-life scenarios.

In this research, we focus on detecting the preceding triggering events to harm, e.g. sudden braking by the vehicle ahead or sudden lane cut-in, as exemplified in Figure 1. In the

Fig. 1: Demonstration of our hazardous event labelling technique, tested on a pre-labelled simulation benchmark, GTACrash. The triggering event was detected using vehicle kinematics and calculated safe distances.

space of hazardous event detection, there are many opposing formulations that range in complexity but lack consensus. Equally for model training, there is a vast volume of naturalistic datasets but lack hazardous scenes labels, as such scenes are hard to quantify when harm is not materialised. Without a standard, labelling remains inconsistent and alter the features that models learn.

As more automated driving functions are added, the subsequent hazardous events to consider grow immensely. The need to generalise harmful events or learn novel event features is highlighted in the early works reviewing external hazard detection [4]. To learn novel hazardous event features, datasets are available but remain scattered in the literature. Alternatively, to generalise events, a vast number of proposals exist; however, few focus on the metrics to detect triggering events. For example, in [5], methods are categorised as time-based, kinematic-based, statistics-based and potential field-based. Yet, the methods do not focus on generalising potential sources of harm but evaluate specific events in terms of likelihood and severity. However, in the work of [6], a more focused metric review is taken to detect hazardous events given no collision. Still, the metrics presented overly conservative idealised safety metrics, which are unrealistic for dataset annotation as actual driving does not reflect such caution. Therefore, we must draw light to more absolute measures to signify the triggering events.

With these current gaps and limitations, this paper aims to provide a concise overview of hazardous event detection metrics, give intuition to their formulation and provide a consensus by proposing metrics to standardise dataset annotation and demonstrating an annotation technique, as shown in Figure 1. We give readers an overview of actor-focused hazard datasets for model training and discuss their utility

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and limitations for existing datasets. As such, the novel contributions for this paper are as follows:

- A novel focus on near-miss hazardous events, as literature is dominated by collision-based events. Yet, most hazardous scenarios we face do not materialise harm.
- Novel overview of near-miss event detection metrics.
- Proposed event-agnostic metrics to detect actor-based hazardous events early and standardise dataset labelling.
- Novel overview of hazard-focused datasets.
- A demonstration of a configurable framework for hazardous event detection and dataset annotation.

The rest of the paper is structured as follows: Section II covers key terminology, detection metrics, proposed metrics and datasets for training. Section III describes our hazardous event labelling technique. Section IV discusses our contribution, limitations and future work. Finally, Section V concludes the paper.

II. LITERATURE REVIEW

A. Hazard Definition and Categorisation

As aforementioned, a hazard refers to a potential source of harm [2], [3]. However, a hazard in isolation does not cause harm, it is the combination of a hazard and the operational situation [2], [3] (e.g. sudden braking by a lead vehicle).

Furthermore, hazardous event detection refers to identifying potential sources of harm and not assessing them in terms of likelihood and severity, which is defined as risk [2]. Specifically, we focus on triggering events, which are the preceding events to harm as crashes are rare, and near-miss scenarios are common, but difficult to quantify.

It is estimated that 83-94% of traffic accidents are due to human error [7], [8], and as such, we focus on hazards derived from surrounding traffic participants (e.g. vehicles, pedestrians), which we refer to as actors. We then subdivide actors into Motor Vehicles (e.g. cars, lorries, motorcycles) and non-motor Vehicles (pedestrians, cyclists and animals).

The differentiation between motor and non-motor vehicles is their freedom of movement. Due to the structured driving domain, motor vehicles are typically easier to predict as they must follow defined lanes and regulations. In contrast, non-motor vehicles have more movement freedom, can rapidly change direction, and do not always follow regulations.

B. Hazardous Event Metrics

Hazardous events are generally related to collisions and are widely applied to collision avoidance systems (CAS). We take a novel focus on triggering events and review the metrics to generalise such events. We investigate two key formulations for kinematic and safe gap-based metrics, as shown in TABLE I. Kinematic attributes are popular to indicate evasive manoeuvres, and safe gap-based metrics calculate safe spatial or temporal thresholds in the longitudinal or lateral direction around the ego vehicle.

Kinematics-based describes the triggering event occurrence by associating ranges of abnormal behaviour in case of a hazard. For example, in [9], the range of deceleration when the lead car suddenly brakes is defined between -4

and -7.5 m/s^2. In other words, when deceleration exceeds a certain threshold, it can signal a triggering event. Other kinematic attributes are characterised between normal and aggressive behaviour in [10]; these attributes include lateral acceleration/jerk to identify triggering events as, e.g. lane departure, evasive lane change, and control loss on bends.

Safe Gap-based qualifies a hazardous event by comparing the actual gap to a hazard with a safe threshold gap. Safe gaps can be represented in the spatial or temporal domain. The threshold value can be pre-set or calculated based on segments describing the sequence of events from detecting a hazard to acting (e.g. applying brakes). The safe distance segments in literature [11]–[14] can be summarised by:

- Safety Margin (D_{min}) refers to the minimum distance to keep from hazards, specifically when ego vehicle is stationary but still keep a clearance.
- Thinking Distance (D_{think}) refers to the distance travelled from hazardous event detection to the execution of action to avoid/mitigate harm.
- Acting Distance (D_{act}) refers to the distance travelled from actuation of the planned action until it is completed (e.g. from starting to brake until the safe distance is restored or standstill state is reached).

Three cases were identified in the literature, the first for longitudinal safe distance in [11]–[13] that shall be kept

TABLE I: HAZARDOUS EVENT METRICS

Category	Kinematic	Safe Gap
Intuition	$x > threshold$ $x < threshold$	**Case 1:** $D_{actual} < D_{safe}$ **Case 2:** $D_{actual} > D_{safe}$ $D_{safe} = [D_{min}, D_{think}, D_{act}]$ **Case 3:** $\text{TTE}_{predicted} \begin{cases} < TTE_{threshold} \\ > TTE_{threshold} \end{cases}$
Metric	**Deceleration** $x = a_{long,dec}$ $x < -4\text{m/s}^2$ **Lat Accel.** $x = a_{lat,acc}$ $x > 4\text{m/s}^2$ **Lat/Long Jerk.** $x = j_{long,lat}$ $x > 0.9\text{m/s}^2$	**Case 1: Long. Safe Distance** $D_{safe_1} = D_{think} + D_{act}$ $D_{safe_2} = \max(D_{safe_1}, D_{min})$ $D_{safe_3} = D_{min} + D_{act}$ **Case 2: Lat. Safe Distance** $D_{safe_4} = D_{virt\_lane\_border}$ **Case 3: Time-To-Event** $\text{TTE}_{predicted} \begin{cases} < 0.5\text{s, hazardous} \\ > 2\text{s, safe} \end{cases}$
Pros	Fast processing with no minimal calculations required.	Makes live dynamic calculations using the real measurement of potential hazards and their effect on the environment.
Cons	Short detection time as it signals immediate evasive manoeuvres.	Safe distances generally consider overly conservative safety margins, which may lead to a high rate of false positives, as drivers leave very small gaps in real scenarios.

from a lead vehicle/object and is applicable in CAVs such as adaptive cruise control (ACC) or automatic emergency braking (AEB). The safe distances formulated in [11], [12] considers ideal situations with reaction time by ego and lead vehicle and the required braking distance with the difference that [12] impose a safety margin. The ideal safe distance results in a long gap to be maintained to lead vehicles is inspired by Rule 126 of the UK Highway Code [15] but is not a realistic value applied by drivers on daily driving tasks.

The second case in [14] defines the lane centre as the reference position, and virtual lane boundaries are defined on each side that is the equivalent of a safe distance. Then, a lane departure type of hazardous event is triggered whenever the ego vehicle's actual distance from the lane centre is greater than the safe distance. This definition is used for application on lane-keeping assist systems (LKAS).

The third case is based on time-to-event (TTE) and the event of interest in [16] is a collision, making this metric time-to-collision (TTC). This metric takes the time required for the vehicle to reach the event of interest and either uses a threshold to signal initiation or expert review. TTC is the most popular metric which assumes that a collision might occur, an assumption which can be made due to the implicit prediction uncertainty.

C. Datasets

To train future systems to detect actor-based hazardous events will require annotated datasets that label the collision or near-miss scenes and include vehicle kinematic, to accurately track vehicle motion as they evolve in time. This has been a challenge as most hazard-focused datasets from real scenes only consist of video data that lacks kinematic data.

Due to a lack of kinematic attributes, researchers have turned to simulation environments such as CARLA [24]; however, actors do not respond realistically. Therefore, sophisticated game engines have also been used to create dynamic actors that automatically perform evasive manoeuvres and follow traffic rules, such as the GTA game engine in the works of [22], [17].

Hazard focused datasets in the literature can be categorised by actor categories and their source, either from real-life or simulation, as compiled in TABLE II.

Of the *motor vehicle* (e.g. car, van, lorry) datasets, these contain scenes captured either from dashcam or simulation.

TABLE II: ACTOR-BASED HAZARD DATASETS

	Data	Scenes (Haz — Safe)	Time (s)	Label Scheme
Real Scenes	A3D[0123] [17]	620 — 1130	5	TTC
	AAD[012] [18]	1500 — 0	2–20.8	TTC
	Collision[012] [19]	803 — 0	40*	TTC
	NIBD[012] [16]	4595 — 0	10-15	Decel.
	CCD[0] [20]	1500 — 0	5	TTC
	TAB[0] [21]	1935 — 0	17.7*	TTC
Sim.	GTACrash[013] [22]	7720 — 3661	2	TTC
	VIENA[01] [23]	1200 — 0	5	TTC

[0]Motor-Vehicle — [1]Pedestrian — [2]Cyclist — [3] Animal — *Average

Of the dashcam footage, NIBD [16] is the largest with 4.5k near-miss clips each 10-15s long. Of the simulation-based datasets, GTACrash [22] and VIENA [23] are popular for GTACrash's vast volume of 10k scenes and VIENA's diversity of actor and scenario types. As all edge cases cannot be guaranteed, CARLA [24] is a popular simulation platform to build custom scenarios but is limited by simulated sensory information and unrealistic surrounding actor behaviours. Regarding the *non-motor vehicle* datasets, this category includes pedestrians, cyclists and even animals in A3D [17] and GTACrash [22]. In general, the datasets have good scene diversity between area types (e.g. urban, highway), as seen in NIBD [16], A3D [17], Collision [19]. Scene diversity is important for models to review various traffic conditions that vary by area and see location-specific hazardous events such as children crossing the street sporadically in residential areas. The datasets exhibit a good contrast between day and night illumination and a slight variation in weather conditions, as shown in NIDB [16], A3D [17] and Collision [19]. Varying environmental conditions are vital to train models on worst-case weather scenarios that cause sensor impairment or poor illumination in dark scenes.

However, the datasets are primarily based on collision scenes, which do not make up most hazardous events. Only NIBD [16] included near-misses by recording scenes based on deceleration events to spot potential harm. Furthermore, there is a mixed case in annotation procedures for each dataset. The majority used variations of TTC with human review to label. The lack of standardisation means inconsistency between datasets, resulting in varying model biases.

Furthermore, there is a mixed case of dataset balance. The majority of datasets include only hazardous event scenes and others being split, 7:3 hazardous/safe split in GTACrash [22] and 6:11 in A3D [17]. Balance is crucial as hazardous scenes are rare in real driving; thus, the balance must be considered to avoid introducing incorrect model biases.

III. METHODS

A. Proposed Metrics

This study proposes metrics to detect actor-based hazardous events, even in the case of near-misses. Given overly conservative metrics and inconsistent dataset labelling, we propose a set of event-agnostic metrics exploiting kinematics to detect evasive manoeuvre early and safe gap-based metrics to establish a minimum safe distance around the ego.

Regarding the *safe gap-based* metrics, we establish a minimum safe distance around the ego vehicle. The proposed formulation for longitudinal direction shall overcome the unrealistic distances defined in the literature. Therefore we target the acting distance identified as *braking distance* in Equation 1, and tune deceleration using both normal driving ranges as in [11], [13], and maximum feasible deceleration by a passenger car, similar to acting distance component in [12]. Therefore, the Equation is formulated as follows:

$$d_{safe}^{long} = \frac{\left(V_{ego}^{long} - V_{target}^{long}\right)^2}{2\,\mu\,|a_{max}|} + max\left(t_{gap}\,V_{target}^{long}, d_{min}^{long}\right) \quad (1)$$

where;

d_{safe}^{long} : the longitudinal safe distance,

v_{ego}^{long} : the actual longitudinal velocity of ego vehicle,

v_{target}^{long} : the longitudinal target velocity from the actor ahead,

μ : the friction coefficient from road surface to ego vehicle tire,

a_{max} : the maximum feasible deceleration by ego vehicle that is proposed a value of -8 m/s² in [25],

t_{gap} : the minimum time gap to keep from actor ahead and the value 0.5s is proposed, which follows the hazardous value defined in [16],

d_{min}^{long} : the minimum distance to keep when ego target velocity is 0 km/h, its value is proposed to 5m as suggested in [15].

To illustrate this metric, we consider a scenario with the ego vehicle driving at 80 km/h (∼22.2 m/s) with an actor ahead driving at 72 km/h (20 m/s). Applying Equation (1), We assume an ideal dry road (i.e. $\mu = 1$), which gives a resulting safe distance of ∼10.3 metres, while the suggested by Highway Code [15] for 80 km/h is 53 metres (∼414% higher). Our safe distance represents a more realistic distance of drivers in real traffic as the braking distance considers the velocity difference with respect to the lead vehicle.

The proposal for lateral safe distance consists of a calculation dependent on current ego velocity and an upper and lower bound, formulated in Equation 2.

$$d_{safe}^{lat} = \max \left\{ \min \left[\left(\begin{array}{c} V_{ego} \sin{(\Psi_{max})} \\ +V_{target}^{lat} \end{array} \right) t_{gap}, d_{max}^{lat} \right], d_{min}^{lat} \right\} \quad (2)$$

where;

d_{safe}^{lat} : the lateral safe distance,

v_{ego} : the absolute velocity of ego vehicle,

t_{gap} : the minimum time gap to keep laterally from actor,

Ψ_{max} : the max yaw angle when moving laterally set to ∼12° in [26],

d_{max}^{lat} : the upper bound is used as a threshold to detect a hazardous event. An initial value of 1.5 metres was defined as reference to the requirement of distance to cyclists in [27]. Further analysis is required to optimise this value.

d_{min}^{lat} : the lower bound that limits the lateral safe distance to a minimum of 65 cm since the minimum lane width in the UK is 3.3m [28] that given an average passenger car width of 2 metres leads to an unoccupied space on lane of 1.3 metres, splitting half each side results ins 65 cm.

This formulation was based on lateral safe distance in [29], with the intention to calculate the lateral distance that ego would travel when suddenly changing its heading by Ψ_{max}, whilst applying some constraints of minimum and maximum lateral distance to avoid under or overestimation.

Regarding the *kinematic-based* metrics, we select deceleration, acceleration and jerk to detect hazardous events in a generalised form, using previously studied abnormal ranges to signal triggering events, as shown in TABLE III.

TABLE III: PROPOSED KINEMATIC METRICS

Kinematic Attribute	Triggering Event Condition	Kinematics Target Values
Longitudinal Deceleration	$a_{(dec)}^{long} < Target\_Value$	-4 m/s² [9]
Lateral Aceleration	$a_{(acc)}^{lat} < Target\_Value$	-4 & 4 m/s² [9]
Longitudinal Jerk	$j^{long} < Target\_Value$	-0.9 m/s³ [10]
Lateral Jerk	$j^{lat} < Target\_Value$	-0.9 & 0.9 m/s³ [10]

By deriving a set of metrics, we hope to provide the framework to generalise the detection of hazardous events, making it possible to systematically annotate large datasets to train models to understand such events.

B. Hazardous Event Annotation Technique

We propose the pipeline presented in Figure 2 to create a hazardous event annotator. The figure shows that the annotator only requires basic information regarding position, velocity, time and direction, like rotation matrix or yaw value, to calculate all necessary metrics and perform labelling. To make the technique as data-agnostic as possible, we perform all calculations to compute vehicle kinematics, as they are typically not available in public datasets. A sliding window with length of three frames is moved with stride value one to calculate actor acceleration, heading, and jerk metrics. The selection of the frames can be adjusted based on the sampling rate of the selected dataset. Having calculated the kinematics for each actor, we rotate all values by (360°- ego vehicle angle) to standardise the lateral and longitudinal axes around to the ego vehicle perspective.

After actor kinematics are calculated and rotated, the data is fed to the annotation module to compare against our proposed safety metrics. We use kinematic acceleration, deceleration and jerk to detect evasive manoeuvres and dynamically calculate longitudinal and lateral safe distances between the ego vehicle and each actor. Subsequently, the system labels a scene is hazardous if any of the kinematics-based metrics are flagged or if the longitudinal and lateral safety distances are both violated to avoid cases of vehicles overtaking in the same direction but different lanes.

Subsequently, our system can take in unlabelled datasets and annotate each frame and scene as hazardous or safe. The input parameters for annotation can be tuned to reflect user preferences or factors in driving conditions, such as friction coefficient in differing weather or road types.

We have tested the system with the GTACrash dataset to observe its behaviour on an annotated dataset. This process aims to shed light on the vulnerabilities of each metric for future improvements. For this reason, 3600 crash scenes are sampled from the GTACrash as crashes are known hazardous events. In addition, to show that the metrics can detect hazardous cases even if the harm is not materialised (near-miss), the collision frames are removed. It shall be also noted that non-crash scenes could not be used due to the lack
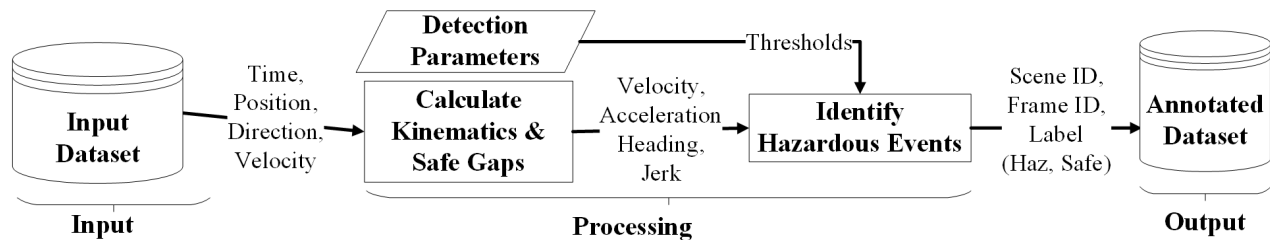
Fig. 2: Dataset annotation flowchart

TABLE IV: ACCURACY ON NEAR-MISS SAMPLES*

Kinematic		Safe-Gap	
Metric	*Result (%)*	*Metric*	*Result (%)*
Long. Decel.	6.06	Long. Safe Distance	88.47
Lat. Accel.	26.97		
Long. Jerk.	98.13	Lat. Safe Distance	96.08
Lat. Jerk.	73.92		
Combined 99.52%			

*Generated by removing collision frames from crash scene sequences to simulate near-miss detection.

of labels of near-miss events. TABLE IV summarises the annotator's ability to label hazardous scenes from GTACrash. TABLE IV shows that the acceleration focused kinematic-based metrics can detect roughly 27%, the jerk focused ones achieve up to 98%, and the safe gap-based metric annotates up to 96.08% of the hazardous cases. Alternatively, when the proposed combined method is utilised, the system detects 99.52% of all hazardous events.

Interestingly, the results in TABLE IV show that the proposed metrics individually cannot annotate all hazardous cases, but synergise when used in combination. There are a few possible reasons why this is the case. Firstly, the GTACrash dataset uses the game GTA5 to generate the dataset where the reasoning of the actors in case of a hazardous event is limited. To illustrate, it is possible for the ego vehicle not to perform an evasive manoeuvre even if a vehicle appears in front. Additionally, it is possible to crash from different sides, with varying headings, which can be missed by either the longitudinal or lateral safe distances.

All in all, the proposed metrics detected around 99.5% of simulated near-miss cases and are implemented in a modular way to adapt to different operational domains.

IV. DISCUSSION

For this study, we have taken a novel focus to detect potential sources of harm, including non-collision-based hazardous events. Given a focus on collision-based events and inconsistent dataset labelling methods, the first task evaluated existing metrics to detect the triggering events preceding harm. After discovering overly conservative metrics with unrealistically large safety gaps, our first contribution proposes objective metrics to detect triggering events in a robust and more realistic formulation. We do this by correlating abnormal values from vehicle kinematics where drivers perform evasive manoeuvres and dynamically calculate more realistic safe gaps around the vehicle to avoid false positives.

The second contribution refers to the definition of a near-miss labelling framework to label datasets using the proposed hazardous event detection metrics. To which, we demonstrate performance on the simulation-based benchmark, GTACrash [22] with promising preliminary results of ($\sim$99.5%) accuracy for hazardous event detection.

Moreover, we discuss the limitations and future work to expand the scope of hazard categories considered, the detection metrics proposed, and the annotation framework.

Hazard Categories: This research focused on actor-based hazards, but it can be expanded to consider other external factors such as environmental and regulatory rules. For example, static environmental factors, such as sharp turns and dynamic factors like road debris or adverse weather, can make road surfaces slippery or limit visibility. Similarly, regulatory hazards could encompass understanding traffic laws to detect surrounding violations that could signal potential harm or avoid ego violation. Alternatively, it is possible to extend annotation to internal hazards, such as input degradation and system failures, given appropriate metrics.

Hazardous Event Metrics: The aim of the proposed metrics was to detect triggering events involving actor-based hazards. Given further hazard categories, environmental effects could be considered to factor in the friction coefficient to weather conditions or road curvature to detect triggering events when driving on bends. The utility of the metrics can also be further expanded to safety check the outputs of motion planning for safer decision-making models.

Annotation Technique: This study aims to present an dataset annotator, which only needs vehicle position and velocity data to derive the necessary kinematics and annotate the scenes provided. Although the preliminary results are promising on annotating simulated near-miss events, it is not possible to draw conclusions for performance on safe scenes, as near-misses are unlabelled. Hence, further exploration is needed to evaluate the performance of the proposed annotator robustly. In addition, as the bulk of datasets contain only perception data, future work could investigate translating perception input to relative positions and velocities, so that the system can extend to all datasets, since actor kinematics are usually not provided.

Situation Awareness: Although the proposed system aims to provide a generic solution to hazardous event annotation, there are certain cases where the context affects whether the

safe distances are applicable (e.g. actors travelling in the same direction, but in other lanes). Current metrics have limited context as they only consider the heading and the distances between vehicles. Thus, future work could explore how to program in a higher level of context-awareness to provide more realistic annotations.

Benchmark Hazardous Event Dataset: In this study, we have utilised the simulation-based GTACrash dataset as it contains detailed vehicle kinematics (i.e. position, velocity) about each actor and labelled crash events. However, since simulations are not realistic and crashes are not the only type of hazardous event, a realistic near-miss benchmark dataset is required and remains a gap in the literature for hazardous event detection. For this purpose, our labelling technique allows researchers to annotate a real-life dataset using the proposed annotation scheme to generate a realistic benchmark for training near-miss events.

V. CONCLUSION

The development and testing of advanced driver assistance systems on public roads have been increasing rapidly in recent years. Such systems need to operate safely in very dynamic and hazardous domains. Safe functionality requires a robust understanding of hazardous events that are not limited to collisions but also include the events preceding a crash, referred to as triggering events (e.g. sudden braking by the vehicle ahead or unintended lane departure).

This study takes a novel approach to detect potential sources of harm, including non-collision-based hazardous events, which are difficult to quantify. Given event-specific metrics, inconsistent dataset labelling and collision-focused events, we contribute a set of generalised hazardous event detection metrics that synergise vehicle kinematics to detect evasive manoeuvres early and safe gaps to calculate minimum safe distances dynamically. These metrics then formed our standardised dataset annotation technique.

Our proposed hazardous event labelling technique is designed to be configurable, to detect collisions and near-miss hazardous events in different operational domains utilising our event-agnostic detection metrics. We show 99.5% accuracy in detecting simulated near-miss scenes in our preliminary tests on a labelled simulation benchmark, GTACrash. Although, given the diversity of scenarios and lack of labelled near-miss datasets that guarantee safe scenes, there is further work to validate robustness. By generalising hazardous event detection and enabling automatic dataset labelling, we provide an important first step to identify harm earlier and obtain the datasets to learn such events at scale.

REFERENCES

[1] World Health Organization, "Global status report on road safety 2018," Geneva, 2018.

[2] International Organization for Standardization, "ISO 26262-1:2018, Road vehicles — Functional safety," Geneva, Switzerland, 2018.

[3] International Organization for Standardization, "ISO 21448:2019 Road vehicles — Safety of the intended functionality," Geneva, 2019.

[4] S. Dogramadzi, M. E. Giannaccini, C. Harper, M. Sobhani, R. Woodman, and J. Choung, "Environmental hazard analysis-a variant of preliminary hazard analysis for autonomous mobile robots," *Journal of Intelligent & Robotic Systems*, vol. 76, no. 1, pp. 73–117, 2014.

[5] Y. Li, K. Li, Y. Zheng, B. Morys, S. Pan, and J. Wang, "Threat Assessment Techniques in Intelligent Vehicles: A Comparative Survey," *IEEE Intelligent Transportation Systems Magazine*, vol. 13, no. 4, pp. 71–91, 2021.

[6] C. Wang, Y. Xie, H. Huang, and P. Liu, "A review of surrogate safety measures and their applications in connected and automated vehicles safety modeling," *Accident Analysis and Prevention*, vol. 157, no. April, p. 106157, 2021.

[7] UK Government, "Road accidents and safety statistics," 2020.

[8] US Department of Transportation, "Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey (2018)," Washington, 2018.

[9] H. Saptoadi, "Suitable Deceleration Rates for Environmental Friendly City Driving," *International Journal of Research in Chemical, Metallurgical and Civil Engineering*, vol. 4, no. 1, pp. 2–5, 2017.

[10] I. Bae, J. Moon, and J. Seo, "Toward a comfortable driving experience for a self-driving shuttle bus," *Electronics (Switzerland)*, vol. 8, no. 9, pp. 1–13, 2019.

[11] S. Shalev-Shwartz, S. Shammah, and A. Shashua, "On a Formal Model of Safe and Scalable Self-driving Cars," pp. 1–37, 2017.

[12] X. Zhang, W. Shao, M. Zhou, Q. Tan, and J. Li, "A scene comprehensive safety evaluation method based on binocular camera," *Robotics and Autonomous Systems*, vol. 128, p. 103503, 2020.

[13] K. Kreutz and J. Eggert, "Analysis of the generalized intelligent driver model (GIDM) for merging situations," *IEEE Intelligent Vehicles Symposium, Proceedings*, vol. 2021-July, no. Iv, pp. 34–41, 2021.

[14] Y. Bian, J. Ding, M. Hu, Q. Xu, J. Wang, and K. Li, "An Advanced Lane-Keeping Assistance System with Switchable Assistance Modes," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 1, pp. 385–396, 2020.

[15] Department of Transport, "The Highway Code," 2022.

[16] H. Kataoka, T. Suzuki, S. Oikawa, Y. Matsui, and Y. Satoh, "Drive Video Analysis for the Detection of Traffic Near-Miss Incidents," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, may 2018, pp. 3421–3428.

[17] M. S. Aliakbarian, F. S. Saleh, M. Salzmann, B. Fernando, L. Petersson, and L. Andersson, "Viena^2: A driving anticipation dataset," in *Asian Conference on Computer Vision*. Springer, 2018, pp. 449–466.

[18] F.-H. Chan, Y.-T. Chen, Y. Xiang, and M. Sun, "Anticipating accidents in dashcam videos," in *Asian Conference on Computer Vision*. Springer, 2016, pp. 136–153.

[19] R. Herzig, E. Levi, H. Xu, H. Gao, E. Brosh, X. Wang, A. Globerson, and T. Darrell, "Spatio-temporal action graph networks," *ICCVW 2019*, pp. 2347–2356, 2019.

[20] W. Bao, Q. Yu, and Y. Kong, "Uncertainty-based Traffic Accident Anticipation with Spatio-Temporal Relational Learning," in *Proceedings of the 28th ACM International Conference on Multimedia*. New York: ACM, oct 2020, pp. 2682–2690.

[21] T. You and B. Han, *Traffic Accident Benchmark for Causality Recognition*. Springer International Publishing, 2020.

[22] H. Kim, K. Lee, G. Hwang, and C. Suh, "Crash to not crash: Learn to identify dangerous vehicles using a simulator," *Proceedings of the AAAI Conference on Artificial Intelligence*, pp. 978–985, 2019.

[23] Y. Yao, M. Xu, Y. Wang, D. J. Crandall, and E. M. Atkins, "Unsupervised Traffic Accident Detection in First-Person Videos," *IEEE International Conference on Intelligent Robots and Systems*, pp. 273–280, 2019.

[24] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, "CARLA: An Open Urban Driving Simulator," in *CoRL*, 2017, pp. 1–16.

[25] P. Mika, "Adaptive car following model," *Strojnícky časopis-Journal of Mechanical Engineering*, vol. 68, no. 3, pp. 281–288, 2018.

[26] G. Ghaffari, K. Brolin, D. Bråse, B. Pipkorn, B. Svanberg, L. Jakobsson, and J. Davidsson, "Passenger kinematics in Lane change and Lane change with Braking Manoeuvres using two belt configurations: standard and reversible pre-pretensioner," *IRCOBI*, pp. 493–511, 2018.

[27] A. Mar, S. Moll, L. Griselda, and A. Garc, "Driver Behavior When Overtaking Cyclists Riding in Different Group Configurations on Two-Lane Rural Roads," 2021.

[28] Highways England, "CD 127 Cross-sections and headrooms," 2020.

[29] D. Qu, X. Chen, W. Yang, and X. Bian, "Modeling of Car-Following Required Safe Distance Based on Molecular Dynamics," *Mathematical Problems in Engineering*, vol. 2014, pp. 1–7, 2014.