# POTENTIAL OF INFRASTRUCTURE-BASED SENSORS TO ROAD SAFETY

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## ABSTRACT

Recent developments in sensor and computer technology enable roadside units not only to monitor traffic flow, but also to process the collected data to improve road safety. This paper presents an implemented test field with a structure of its use cases ranging from traffic monitoring to advanced extended perception utilizing a vehicle to infrastructure communication techniques. The traffic monitoring use case can be extended with an automatic accident detection being performed in a road-side unit. The accident detection method is to identify a potential accident in near real time in order to activate the first responders without unnecessary delay. The proposed vehicle-to-vehicle accident detection method is based on the evaluation of sudden velocity vector differences. The vehicles are recognized using the YOLO method from the video stream and the optical flow method is used to evaluate the sudden velocity changes, which are classified in order to decide about a possible accident.

**Keywords**: Road safety, Infrastructure sensors, Automatic accident detection, Roadside unit, v2x, v2i, Occlusion.

## 1. MOTIVATION

The World Health Organization (WHO, 2023) estimates that in 2021, approximately 1.19 million people worldwide lost their lives due to road traffic accidents, with 92% of all fatalities occurring in low- and middle-income countries, including all countries on the African continent. While the average number of fatalities on European roads is seven per 100,000 inhabitants, the figure for Africa reaches dismal 19.4.

Road safety requires a holistic approach, defined by the so-called Safe System Approach (EC 2022, US DoT, 2022), in which system providers bear the ultimate responsibility for preventing serious consequences of system use. The Safe System Approach is defined by the following pillars:

- Safe speeds.
- Safe infrastructure.
- Safe vehicles.
- Safe road user behaviour.
- Post-crash care.

The EU-funded TRANS-SAFE project[1] aims to maximise the impact of road traffic safety solutions by bringing together road safety agencies and experts from Europe and Africa

[1] https://www.trans-safe.org/

together to drive various actions. The project covers all pillars of the Safe System Approach at the analytical and practical levels.

Post-crash care involves medical attention after a traffic accident, including first aid, emergency care, rehabilitation, and recovery. Prompt response improves survival chances and reduces injury severity. Immediate emergency response at the accident scene can greatly decrease fatalities. However, the first responders should be informed about the accident occurrence and its location. This information can be transmitted by vehicles equipped with the Accident Emergency Call Systems (AECS), as defined e.g. in the Regulation UN ECE R144 (UNECE, 2018), i.e. systems that automatically contact the emergency services in the event of a serious accident. An airbag activation is usually used as an indicator for an automatic call. In Europe the deployment of the so-called eCall system started on 1 April 2018 as a public system. In other countries, such as the United Arab Emirates, AECS is required by the authorities or offered as a service by vehicle manufacturers, such as GM and Ford in North America. The application of AECS on vehicles, which were not originally equipped with this system is complicated. There are also some aftermarket telematics devices offered by insurance companies that have a similar capability. However, they are not connected to airbag control units but are based on internal sensors.

Infrastructure-based sensors appear to be an alternative solution for obtaining near real-time information on road accidents. In this case, the systems are independent of vehicle equipment, age or country of origin in the case of imported vehicles. However, such systems require investment to install roadside units equipped with sensors and to process the sensor data. The investment can be reduced in places where traffic monitoring systems are already installed, e.g. at critical intersections or test fields. In such a case, only an application unit, an edge computer, needs to be added to run automatic accident detection algorithms. This paper presents test-field example and development of automatic accident detection to be implemented in the test field.

## 2. STATE-OF-THE-ART

### 2.1 Test Field Strategies

Recent developments in communication, perception and computing technologies are enabling an increasing number of applications based on infrastructure-based systems to support road users and road infrastructure providers. Although many intersections and road sections are equipped with camera-based surveillance technology, infrastructure-based technology test fields are intensively used for research and development purposes with different objectives.

In Germany alone, the overview for 2021 shows 26 test sites with different focuses (BASt, 2021). Another overview of test fields is given in (Creß et al. 2024), where the authors identify 53 projects dealing with the development of different test fields in different parts of the world. Very often the test fields are focused on the application of vehicle to everything (v2x) communication technology, such as AUTOCIS (Naranjo et al., 2018) or InterCor (Krämmer et al., 2022).

Other test fields also install roadside units equipped with sensors, very often cameras, such as the Niedersachsen test field (Köster et al., 2018) or the Baden-Württemberg test field (Fleck et al., 2018). Another category of test fields uses several types of sensors, such as cameras, radars or lidars, and performs a fusion of the data to obtain more reliable results, e.g. Providentia++ (Krämmer et al., 2022) or Test Field First Mile (Song et al., 2024). This approach should eliminate the disadvantages of specific sensors.

### 2.2 Automatic Accident Detection

Vehicle accident detection methods have grown from traditional programming to automated classification by trained algorithms on infrastructure-based data, in particular from cameras. An overview of some of the available approaches, including their evaluation, is presented in (Sabry and Emad, 2021), for example. One of the first approaches to automatic accident detection is presented in (Ki and Li, 2007) using traditional methods of background subtraction and vehicle area tracking. They detect moving vehicles using frame differencing, binarisation and projection, then estimate their state based on position, area, direction and velocity, and identify accidents when thresholds are exceeded.

With increasing computing power, researchers have adopted advanced methods such as optical flow, which quantifies pixel motion, as published in (Sadeky et al., 2012), to analyse vehicle motion and develop an accident probability model using a logistic curve. In a further development (Machaca Arceda and Laura Riveros, 2018), the Violent Flow descriptor was introduced and a learning model was developed to detect car accidents. Violent Flow is derived from the original optical flow concept, which calculates the motion intensity, but focuses on the statistical changes of their motion intensity over a period of time, rather than a frame-by-frame approach. Many approaches are based on object classification methods, very often using convolutional neural networks such as YOLO (You Only Look Once), first published in (Redmon et al., 2016). YOLO is known for its efficiency and accuracy in object localization.

## 3. INFRASTRUCTURE

### 3.1 Test Field "First Mile" Ingolstadt

The First Mile Ingolstadt test field is a unique peri-urban environment for testing connected cooperative automated mobility in the mixed environment of a public road in Germany, which is being built in collaboration with the City of Ingolstadt, industry partners and academia (Song et al., 2024). The test field connects the exit of the Digital Motorway A9 test field with the IN-Campus technology park. It offers approx. 3 km of bi-directional roads, including intersections and urban features, such as bus stops, pedestrian crossings with traffic lights, roundabout, car parks, cycle paths, and sidewalks. The test field is equipped with Road Side Units (RSUs) along the road, fibre optic communications infrastructure and a Mission Control System in the back-end to aggregate all the information and run global applications on it. A map of the test field is presented in Figure 1, where yellow dots indicate the location of masts with RSUs.

The RSUs form the basis for road traffic monitoring and vehicle to infrastructure (v2i) communications, locally processing all infrastructure-based sensor data and communicating local object lists to the Mission Control System via the local communication network, as well as communicating information to vehicles using standardised v2x messages. Each RSU is based on an approximately 4.5 meters high mast with a number of sensors such as cameras, radars and lidars. Selected RSUs are equipped with v2i communication units. In addition, each mast has a control cabinet containing a local processing application unit for the edge computing, a network switch and redundant power supplies. The RSUs have been designed with a flexible combination of different sensing modalities. Figure 2 illustrates an example of the sensors - 2 cameras on the top of the setup facing left and right on the road, 1 camera facing under the mast, 2 lidars below the cameras and 2 radars below the lidars facing left and right on the road.

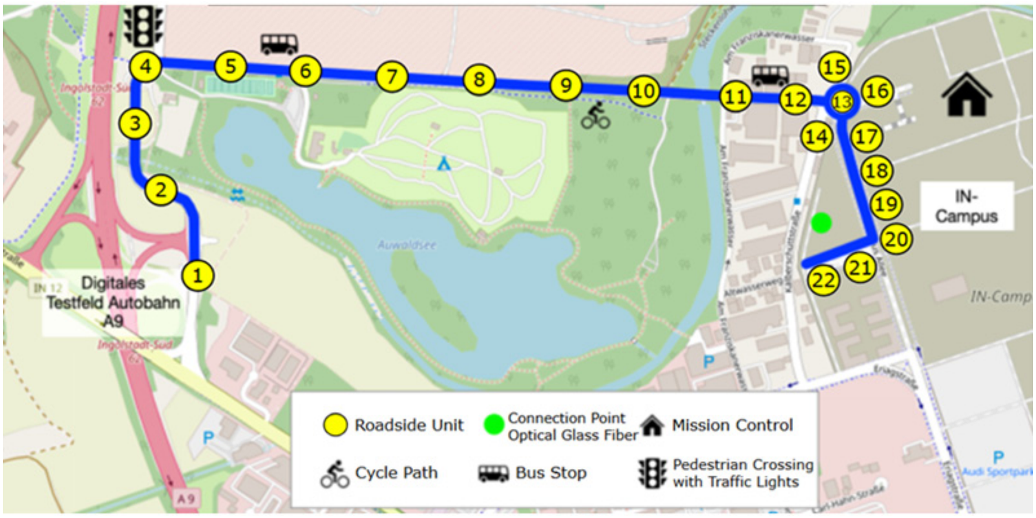


**Figure 1: Test Field "First Mile" Ingolstadt (de Borba et al., 2025)**

All 22 RSUs communicate the local object list to the mission control using a unified protocol with First Mile Object Lists. The basic structure of the data processing and communication within the RSUs and Mission Control is presented in Figure 3. See (Song et al., 2024) for more information on the communication protocols.

**Figure 2: Mast With installed sensors**

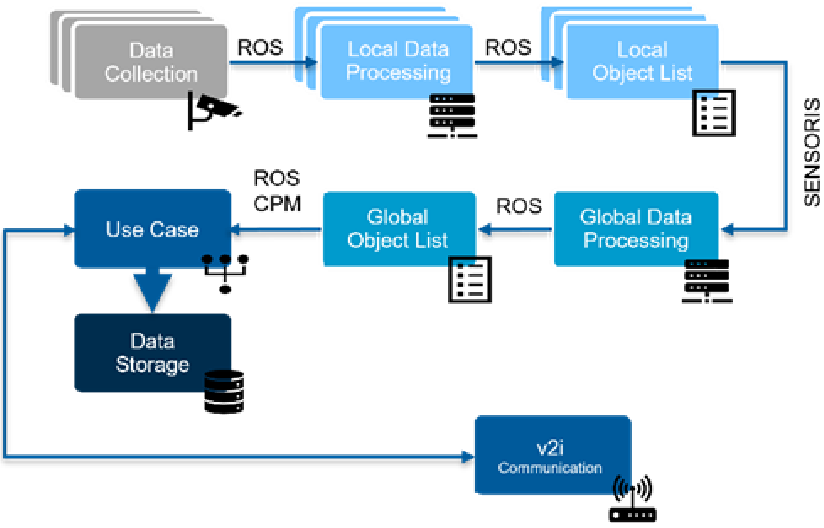


**Figure 3: Basic structure of the First Mile Test Field (Vaculín et al., 2023)**

### 3.2 Basic Use Cases

The use cases of the test field range from passive traffic monitoring, to informing vehicles about objects in their environment, to other levels of cooperation between vehicles and infrastructure, to fusion of data from vehicles and infrastructure in Mission Control System to expand data information sources (data crowd sourcing).

#### *3.2.1 Traffic Monitoring*

The Traffic Monitoring Use Case represents basic monitoring of traffic flow in the test field. It collects data from the test field and creates a dynamic map with their locations and other parameters.

Local object lists are calculated at each RSU. They describe objects such as cars, trucks, bicycles, pedestrians with the following parameters:

- an identifier of the given RSU;
- a local unique object identifier (ID);
- a time stamp;
- an object class; and
- object coordinates including e.g. relative position velocities and heading in the local RSU coordinate system.

Based on the knowledge of the absolute coordinates and heading of the local RSU coordinate systems, the local object lists of all RSUs are fused into a global object list. The aim is to maintain the same object ID for each object throughout its existence in the test field.

Traffic Monitoring collects all the fused global lists in the testbed to provide an overview of traffic in the testbed. The global object list in this use case generates a basis for the following use cases.

Furthermore, local data processing application unit in Figure 3 installed at each mast can be used for the proposed automatic accident detection. The communication infrastructure will be used for alarming the first responder’s operator about the possible traffic accident.

#### *3.2.2 Assisted Perception*

In the case of Assisted Perception, the global object list is sent back to the RSUs and made available via v2x communication to the participating connected vehicles equipped with the relevant on-board communication units. The main advantage is that the participating connected vehicles have better information about the objects they can receive from their on-board sensors. Such objects may, for example, be out of sensor range or occluded for the sensors. The benefit for the participating vehicles is increased confidence in their surroundings and safer generation of vehicle trajectories.

#### *3.2.3 Collaborative Perception*

Many vehicles are equipped with on-board sensors and also generate their own object lists. The position of the vehicles in the test field is also available to the Mission Control System. In collaborative perception, the participating connected vehicles send their object list in their moving local coordinate systems to the Mission Control System via v2x messages to RSUs. The information from the vehicles augments that from the RSU sensors. Such data crowd sourcing adds redundancy to the system and also helps to cover areas where the RSU sensors provide uncertain data. Alternatively, it could lead to a faster increase in object confidence or a reduction in the number of RSUs required to build a global object list.

### *3.2.4 Extended Perception*

The most advanced use case profits from the global object list which goes beyond the range of vehicle on-board sensors and can propose emergency trajectories for the participating vehicles. An example of application is shown by de Borba (2025). This approach also raises the question of liability for decisions taken by the infrastructure.

### *3.2.5 Further Use Cases*

The installed perception systems and edge computing available at the RSUs enable the sensor data to be processed for other purposes. For example, weather warnings based on temperature measurements and icy road warnings from the activation of the vehicle stability control system as vehicle mass data, or accident detection based on the RSU perception sensor data. However, the First Mile test field provides relatively little data for the development and testing of such systems.

## 4. AUTOMATIC ACCIDENT DETECTION

As mentioned in the previous section, automatic accident detection from RSU perception sensor data is possible to be implemented in the test field. The main advantage of such a system is that it requires neither to install any on-board units for v2i communication nor have vehicles equipped with the Accident Emergency Call Systems.

The Automatic Accident Detection is being developed subsequentially. The first phase focuses on virtual development of the accident detection algorithm, specifically the vehicle-to-vehicle accidents.

### 4.1 Approach to the Automatic Accident Detection System

Accident detection from a video stream consists of three steps, which can be described as follows:

The first step is the identification of objects within the images, specifically vehicles in the case presented. This process requires an object detection algorithm capable of locating and classifying objects in each frame. Modern automatic accident detection systems mainly use convolutional neural network-based detectors, such as YOLO, mentioned in Section 2.2.

Once objects have been detected, tracking their movement across video frames is critical to accident detection. Multiple object-tracking techniques are used to assign unique identifiers to detected objects and track them consistently. This process includes object detection and data association, which includes detection assignment, trajectory prediction and trajectory updating. Track prediction uses algorithms such as the Kalman filter to estimate future positions based on observed motion patterns, while the data association process links detections to existing tracks. This continuous tracking process enables the system to build up a profile of each object's movement, which forms the basis for accident detection analysis.

The final stage of accident detection is the analysis of motion patterns to identify potential collisions. Optical flow is a widely used technique for estimating motion by tracking pixel displacement across successive frames. It calculates two key metrics: flow magnitude, which represents motion intensity, and flow angle, which represents direction. In this research YOLOv8 and CUDA based dense optical flow are deployed. The oriented violent flow method calculates flow magnitudes, which are collectively summed into 8 bins according to their angular direction (Gao et al., 2016).

Such methods enable the detection of abrupt changes in motion, which are indicative of potential accidents. The collected motion data are processed by a trained classifier to detect patterns associated with collisions.

### 4.2 Dataset

The classifier must be trained and validated on a dataset with respective video footage to deliver reliable results. The statistical data (Statistikportal, 2025) indicates just five accidents involving passenger cars in the First Mile test field during the last decade. However, for the training and validation one would require thousands of video recordings with and without accidents. As the dataset with the video footage would only contain no-collision cases, it is impossible to use the footage from the RSU cameras for the training, validation and testing.

From this reason, it was decided to use synthetic dataset generated with simulation tools. The simulation package should be able to deliver several features, such as (i) vehicle dynamic motion of a vehicle, (ii) photorealistic scene including photorealistic vehicles, (iii) accident simulation with contact simulation and realistic vehicle deformations.

Many tools cover just one or two of those requirements. There is coupe of vehicle dynamics simulation tools being able to model vehicle dynamics behaviour and offering photorealistic visualisation, but the accident simulation is not included.

The accident is described not only by sudden change in the vehicle velocity and often also orientation, but also by a plastic deformation of the car body. To calculate the plastic deformation of the car body the finite element method is being normally used, but it is a very time-consuming process in the modelling and particularly in the simulation, furthermore, the finite element tools cannot usually generate the photorealistic environment. If the surrogate models are applied, e.g. simplification of the vehicle with couple of masses and force elements, the acceleration behaviour can match pretty well, but the visualisation is not available. After a deep analysis of available tools, one compromise has been found, which offers all three requested features. The tools named BeamNG.tech (Maul et al., 2021) originating in gaming industry fills the niche for such a simulation. The vehicle structure elasticity is modelled with beams and nodes and a threshold for the plastic deformation is added. An example of a scenario is presented in Figure 4, the scene is captured with an infrastructure fixed camera and the vehicles are colliding to each other.

**Figure 4: Example of a BeamNG scenario**

The synthetic dataset generated for this research with BeamNG.tech contains 1,961 video footages with crash, normal traffic and near-miss incidents.

### 4.3 Results

Models are trained and optimized through hyperparameter tuning and precision-recall threshold adjustments to minimize crash miss-detections.

The trained classifier was tested on a dataset with 350 elements, 185 of them were from the non-collision group and 165 resulted in a collision. The efficiency of the systems can be demonstrated by a confusion matrix, in which the classification is depicted as follows:

- True Positive: the correct prediction of a collision.
- True Negatives: the correct prediction of no collision.
- False Negatives: the false prediction of no collision, the correct result is a collision.
- False Positives: the false prediction of a collision, the correct result is no collision.

The confusion matrix presented in Figure 5 demonstrates the strong performance of the trained model, with most instances correctly classified into their actual classes. 167 correctly classified non-collisions and 155 collisions are accompanied only by 18 false positive cases, where the system indicated a collision, although none occurred in the reality, and 10 false negative cases, where no collision was classified, although there was one. The precision of the trained classifier reached a value of about 0.90 for the collision class.

Independent of the quality of the classifier decisions, the alarm should be confirmed by an operator, who will initiate a rescue action.

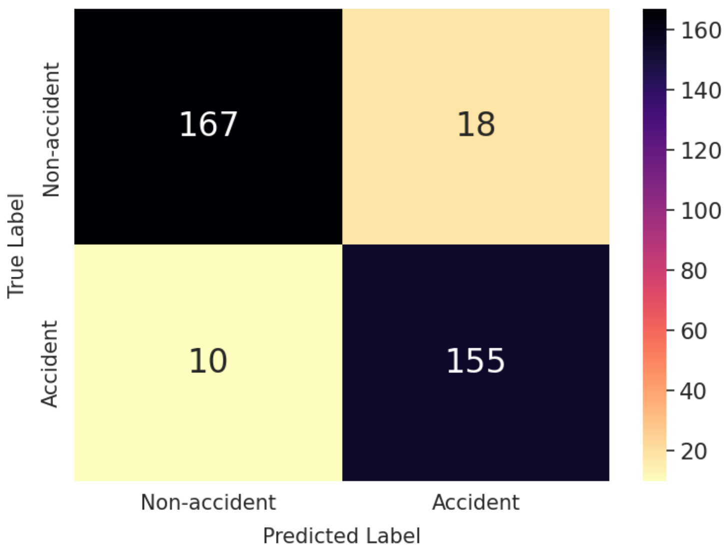


**Figure 5: Confusion matrix**

## 5. CONCLUSION AND OPEN PROBLEMS

Infrastructure-based systems have great potential for improving vehicle safety. The experience from the First Mile Test Field shows various possibilities for intelligent transport systems. However, the implementation of such systems requires certain investments not only in the infrastructure, but also in the vehicles. The use cases presented have the potential to contribute to road safety by providing redundancy of information and/or by improving the vehicle's perception range and mitigating the drawbacks of on-board sensors. Crowd data sourcing is an option that can reduce the number of masts while keeping the information available.

Automatic accident detection is another use case for infrastructure-based sensors. A major advantage of this approach is its independence from the vehicle fleet. Unlike eCall, the proposed automatic accident detection system does not require any equipment in the vehicle, but uses the video stream from the infrastructure-based cameras. This means that it will only work where the cameras are available.

The results of the Automatic Accident Detection system based on synthetic data show very promising detection capabilities for both collision and non-collision classes, with an average precision score of 0.92. The high score underlines the reliability of flow features as a strong predictor for vehicle-to-vehicle crash detection using vision-based data.

Further research should focus on extending the detection algorithms to accidents involving vulnerable road users, and evaluating the method with non-synthetic datasets. Another line of research could be the implementation of the algorithms in vehicle on-board cameras.

## 6. ACKNOWLEDGEMENT

The research that led to the publication of this paper has been supported by the European Union's Horizon Europe Research and innovation funding programme, Grant Agreement No. 101069525 (TRANS-SAFE). Furthermore, the authors would like to acknowledge the kind support of the project IN2Lab by Bayerisches Staatsminiterium für Wirtschaft, Landesentwicklung und Energie under Nr. DIK-2003-0011 // DIK0186/01. The authors would like to thank all colleagues who contributed to the development of the test field First Mile.

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