# AI IN ROADTUNNEL – SUPPORTING THE MAN-IN-THE-LOOP IN ROADTUNNEL (SMART)

<sup>1</sup>Philipp Böhnke, <sup>2</sup><u>Tom Schumann</u>, <sup>2</sup>Dirk Kemper, <sup>2</sup>Alvaro García Hernandez <sup>1</sup>ave Verkehrs- und Informationstechnik GmbH, DE <sup>2</sup>RWTH Aachen University, Lehrstuhl und Institut für Straßenwesen (ISAC), DE

DOI 10.3217/978-3-85125-996-4-26 (CC BY-NC 4.0) This CC license does not apply to third party material and content noted otherwise.

### ABSTRACT

This paper gives an overview about the latest research results of ave company together with the RWTH Aachen University in the field of AI based incident detection. The presented approaches and results were mainly gained in the context of the research project "Supporting the Man-in-the-loop in Roadtunnel (SMaRt)" funded by the German Federal Ministry of Education and Research (BMBF).

The workload of tunnel operators is constantly increasing, leading to overloads and affecting safety. Today's systems for traffic monitoring and incident detection in road tunnels usually follow a two-stage approach. A sensor bases automated incident detection system is followed by "final detection" and/or the cause of the incident by the tunnel operator. Depending on the reliability of the incident detection system used, this means more or less "extra" work for the "man-in-the-loop" – the tunnel operator.

Within the 3-year project SMaRt (2021-2024) AI based methods are developed to improve incident detection and thereby to reduce the workload of the operators. AI is used on three levels, namely the sensor- ("Intelligent Induction Loops" and video), the data fusion- and the GUI-level.

The results show that AI algorithms can help combine loop and video technology to take advantage of both technologies.

Keywords: AI based incident detection; support for tunnel operators; increasing tunnel safety

### 1. INTRODUCTION

Even in an increasingly digitalized world, many decisions are still made manually, i.e. with the direct involvement of a person. Highly complex technical systems and processes are monitored by so-called operators, the people responsible for the process. In the event of a malfunction or alert, the technical system automatically provides the operators with information that enables them to quickly assess the current status of the process, but the operator is still responsible for selecting the necessary and appropriate countermeasures and initiating them. This approach, also known as "man-in-the-loop", is used in various areas of application. In many of these areas, however, the large flood of information and insufficiently adaptive evaluation of the information leads to a constant overload of operators and thus to a reduction in safety. Particularly in the field of public infrastructure, e.g. road tunnels, the approaches used today are still too often based on classic, i.e. non-learning algorithms that no longer reflect the state of the art.

In Germany, but also in Europe, automatic incident detection systems are mainly based on optical (video, infrared, etc.) or electromagnetic (induction loops, etc.) technologies. Both technologies have specific advantages and disadvantages, which are basically due to the underlying physical measuring principles. For example, the "Intelligent Induction Loop"

electromagnetic sensor used in the SMaRt measures very reliably, but has a spatial resolution that corresponds to the distance between two neighboring measurement cross-sections (here: 330-480m). The optical video system used, on the other hand, has a very high spatial resolution, but is not as reliable with regard to shadowing.

Aim of the research project SMaRt is to use innovative artificial intelligence (AI) algorithms to significantly improve the working conditions for operators in road tunnels. This is done by a three-level approach. Therefore, AI should be used namely on

- Senor level ("Intelligent Induction Loop" and video)
- Data fusion level
- Graphical user Interface (GUI) / operator level

### 2. RESEARCH PROJECT SMART

The SMaRt project is founded by the German Federal Ministry of Education and Research (BMBF) within the funding directive "KMU-innovativ: IKT".

Goal of the funding is to strengthen the innovation potential of small and medium-sized enterprises (SMEs) in the field of cutting-edge research and to increase the attractiveness of research funding under the "IKT Fachprogramm". This funding measure is intended to help SMEs establish themselves in the information and communication technology (ICT) market and become more competitive. The aim is to support SMEs that are active in the field of ICT or want to expand and strengthen their business area through the use of ICT [1]. During the 36-month project (July 2021 to July 2024) a test area was set up near the city Aschaffenburg, which includes parts of the tunnel-like noise protection housing "Einhausung Goldbach-Hösbach" on the motorway A3, in the following called Hösbach tunnel (Figure 1).

The SMaRt project team consists of the "ave Verkehrs- und Informationstechnik GmbH", "Lehrstuhl und Institut für Straßenwesen (ISAC) der RWTH Aachen" and, as an associated partner, the "Die Autobahn GmbH des Bundes – Niederlassung Nordbayern". This means that a SME as a developer and manufacturer of automatic incident detection systems, a research institution and an infrastructure provider are represented, so that the entire chain from research to development and implementation to operation is covered.



Figure 1: "Einhausung Goldbach-Hösbach", Source: www.google.de/maps; www.wikipedia.org/wiki/Einhausung\_Hösbach

Acronym	SMaRt	
Full name of the project	Supporting the Man-in-the-loop in Roadtunnel	
Project duration	July 2021 bis July 2024	
Funding directive	KMU-innovativ: IKT	
Funder	German Federal Ministry of Education and Research (BMBF)	
Project Management Agency	DLR Projektträger	
Project partners	oject partnersave Verkehrs- und Informationstechnik GmbHoject partnersRWTH Aachen University, Lehrstuhl und Institut für Straßenwesen (ISAC)	
Associated project partner	Die Autobahn GmbH des Bundes – Niederlassung Nordbayern	

## **3. DESCRIPTION OF THE APPROACH**

## 3.1. Test area Hösbach tunnel

The test area in the Hösbach tunnel consists of three measuring cross-sections with intelligent double induction loops according to TLS Type2 [2]. These three measuring cross-sections form two measuring sections of about 480m and 330m, each of which is limited by two neighboring measuring cross-sections. This covers a total length of approx. 810m of the tunnel with three main lanes and hard shoulder as well as in section 1 an exit and in section 2 an access road (Figure 2).



Figure 2: Schematic layout - test area Hösbach tunnel

In addition, various video cameras are installed in the Hösbach tunnel which provides a good visual overview of the whole tunnel, including the test area.

# 3.2. Used electromagnetic sensor "Intelligent Induction Loop"

As electromagnetic sensors a MAVE<sup>®</sup>-tun R&D system based on the measuring principle of the "Intelligent Induction Loop" was chosen. This sensor enables to collect both local and section-related traffic data as well as local and section-related alerts. Possible alerts are broken down/stationary and slow driving vehicle on the measuring cross section (local) as well as in

the measuring section (section-related). In additional it allows also detecting wrong-way driver and traffic jam.

For the section-related alerts, two neighboring measuring cross-sections are logically combined into one measuring section (Figure 3). As soon as a vehicle enters the measuring section via the entrance cross section, an electromagnetic pattern of the vehicle is recorded. When leaving the measuring section, a second electromagnetic pattern is detected at the exit cross section. By pattern recognition both patterns were correlated. An essential feature of this measuring procedure is to guarantee privacy. This means it is for system-related reasons impossible to identify individual vehicles or drivers [3].

The time difference between the time stamps of the two patterns corresponds to the travel time of the vehicle. As the distance between entrance and exit cross section is structurally defined and known. Thus, the travel speed through the section can be calculated easily. Since the method is applied continuously for each vehicle, the number of vehicles in the section can also be measured. This also enables the calculation of the traffic density. All collected traffic data as well as the resulting alerts are available nearly in real time.

Alerts are detected by comparing the travel time of the individual vehicle with the travel time of the surrounding traffic. Significant differences are an indicator for incidents like broken down, slow or wrong driving vehicles. All significant events cause an immediate change in the current traffic flow. Hence, the detected results indicate an incident of any cause, e.g. a car break down, an accident or a person on the road at a very early stage.



Figure 3: Intelligent Induction Loop technology - measuring principle

Due to the physical measuring principle and its implementation in the Hösbach tunnel the electromagnetic sensor data has a spatial resolution of about 330-480m and a temporal resolution that corresponds to the current travel time for the section.

Even though the conventional MAVE<sup>®</sup>-tun system already works very well and delivers very good results, new detection and evaluation algorithms based on AI are developed within the research project. One aim of SMaRt is to investigate if and if yes to which extent the MAVE<sup>®</sup>-tun system based on the "Intelligent Induction Loop" can be further improved through the use of AI at sensor level.

## 3.3. Used optical sensor "Videocamera"

In order to keep this system cost efficient the developed methods are designed to be applicable to various different camera systems and run on the preinstalled cameras also used by the operators. The test area itself is supplied with full-hd and hd-ready cameras covering the entire tunnel. All video-streams are firstly downsampled to  $320 \times 320$  pixels to keep the

computational cost low while ensuring the proposed system's usability on a wide variety of camera systems.

Due to the relative efficiency and reliability of the induction loop based system the development of the vision based system was centered on effectively validating pre-alerts. As described in chapter 3.1.2 the induction loop alerts are generated if there is an unexpected deviation in traveling times between multiple vehicles e.g. single vehicles having stopped. Due to the time critical nature of the reaction of the operators to potential dangers being caused by incidents in the tunnel [4] this system is designed to detect anomalies as quickly as possible once being triggered. To achieve this task while being energy efficient a two stage system is proposed. The first stage continuously extracts sequences of video frames from the video streams. Using this method a ring buffer of the last five minutes is stored, of which only the last 30 seconds are used for the incident detection.

The optical systems second stage is in its default state on standby, waiting to be triggered by an alert. Once an alert is received a background estimation method is performed on the last seconds of the ring buffer. The estimated background as well as the individual frames are used as input for different anomaly detection methods. The anomaly detection method is derived from [5]. A pre-trained deep neural network is used to extract features given an input image. In a following step the distribution of these deep features is estimated for each camera position and raw frames and background estimated frames. The anomaly score of each image is derived from its feature representations probability in this distribution. Additionally a novel neural network architecture is developed and tested on the dataset. Both architectures are especially suited to work in conjunction with a loop based system.

## 3.4. AI Approach

٠

In the SMaRt research project, AI is to be used to find new solutions that help to speed up the detection of significant anomalies in the traffic flow and thus significantly support the operators - the man-in-the-loop. To detect these anomalies, both the "Intelligent Induction Loop" sensor from the company ave and the video detection/ CCTV system from RWTH / ISAC are used. Innovative AI solutions can be found on three different levels in three different project phases:

•	Phase 1: Stand-alone AI	- on sensor level

- Phase 2: Connected AI (partly) on fusion level
- Phase 3: Connected AI (mainly) on GUI / operator level.

While AI is still independent at the sensor level for the two sensor systems used, the results are connected at the fusion level. The aim here is to confirm or reject early "pre-alerts" from the Intelligent Induction Loop system as quickly as possible, i.e. faster than is possible with the Intelligent Induction Loop system alone, using the video system. If this is possible, time can be saved and road safety increased (Figure 1).

Finally, at the GUI and operator level, the personal preferences of different tunnel operators with regard to alerting by means of AI should be analyzed and taken into account. Not every tunnel operator in every tunnel sees similar anomalies in the traffic flow in the same critical way and wants them to be displayed. For example, slow-moving trucks in underwater tunnels can be "normal" and therefore "undesirable" due to gradients, but in mountain tunnels without a significant gradient they can indicate an "alerts-worthy anomaly" and therefore be "desirable".

12th International Conference 'Tunnel Safety and Ventilation' 2024, Graz



Figure 4: AI the SMaRt approach

## 4. **RESULTS**

### 4.1. Sensor level

Within SMaRt the sensors Intelligent Induction Loop and video / CCTV are used.

### 4.2. Intelligent Induction Loop

AI is used at the sensor level of the Intelligent Induction Loop sensor for pattern respectively vehicle recognition to reduce the dimensions of 1-dimensional vehicle patterns to 8-16 essential dimensions.

The process uses an encoder to generate a coded pattern with lower dimensions from the initial vehicle pattern, which is then decoded into a reconstructed vehicle pattern using a decoder.



Figure 5: Encoder – Decoder

By comparing the initial vehicle pattern with the reconstructed vehicle pattern, a degree of error is calculated which needs to be optimized (Figure 6).

In a further step, the coded patterns of lower dimensions of the input and output measurement cross-sections are compared with each other and assigned. AI is also used here.



Figure 6: Comparison between initial and reconstructed vehicle pattern

## 4.3. Video

The dataset used for the experiments consists of 30 hours of video material of 10 cameras in the 500 m long test area as an input. Data was extracted over five different days while covering all times of day and night. The dataset used for these experiments has been recorded during normal traffic. It consists of almost exclusively ordinary traffic situations and does not include a significant number of incidents for a quantitative evaluation. The only incident that is present in the dataset reaches the highest anomaly score within the entire dataset using the Pre-Trained Deep Features based Anomaly Detection. The same video also shows very promising anomaly scores using our self-developed anomaly architecture. Both methods meet the speed requirement by reaching under 0.1 second response times for current anomalies in all ten cameras simultaneously and a under 1 second response time while detecting anomalies in the past 30 seconds. Both systems do not show a significant correlation between anomaly score and vehicle count in the frame and can be a reliable addition to an induction loop based system.

## 4.4. Fusion level

On the fusion level first results have shown that all alerts forwarded by the loop based system were classified correctly by the video detection system. The experiments ran for a very limited time of a few weeks. During this time there was 1 true positive alert and less than 10 false positives alerts.

## 4.5. GUI / Operator level

Up to now, no results are available for this level. Due to the complex real-time data collection of e.g. desired and undesired alarms, which would have to be carried out by the operators on site, this level will have to be worked on theoretically in large parts at the end of the project.

### 5. SUMMARY AND CONCLUSION

The first results of the research project SMaRt are promising. It appears that a combination of different sensor types (here Intelligent Induction Loop and video) based on physically different measurement principles can be very useful in terms of accuracy and speed of the generated alerts. The use of AI can also help to improve such a system on various levels.

However, it remains to be seen whether the use of different, partly redundant sensor systems for alert detection can be operated economically and thus find a market.

### 6. REFERENCES

- [1] KMU-innovativ: IKT; Forschungsprogramm des Ministeriums für Bildung und Forschung im Bereich Informations- und Kommunikationstechnologien (IKT), https://www.bmbf.de/bmbf/de/forschung/innovativer-mittelstand/kmuinnovativ/kmu-innovativ-ikt/kmu-innovativ-ikt node.html
- TLS 2012; Technische Lieferbedingungen f
  ür Streckenstationen; Ausgabe 2012; Herausgeber: Bundesministerium f
  ür Verkehr, Bau und Stadtentwicklung; Berlin 2012; https://www.bast.de/DE/Publikationen/Regelwerke/Verkehrstechnik/Unterseiten/V5tls-2012.pdf? blob=publicationFile&v=1
- [3] P. Böhnke, P.L. Böhnke, "Intelligente Induktionsschleifen zur automatischen Detektion von Störfällen", Zeitschrift Straßenverkehrstechnik Ausgabe 01/2018, Kirschbaum Verlag GmbH Bonn (Organ der FGSV Köln, BSVI München, FSV Wien), Germany
- [4] J. Versavel, "Road safety through video detection," Proceedings 199
   IEEE/IEEJ/JSAI International Conference on Intelligent Transportation Systems (Cat. No.99TH8383), Tokyo, Japan, 1999, pp. 753-757, doi: 10.1109/ITSC.1999.821155.
- [5] O. Rippel, P. Mertens, E. König and D. Merhof, "Gaussian Anomaly Detection by Modeling the Distribution of Normal Data in Pretrained Deep Features," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-13, 2021, Art no. 5014213, doi: 10.1109/TIM.2021.3098381.