R&D PROJECT TUNNEL SENSOR FUSION

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ABSTRACT

This paper describes the processes and results of an R&D project implemented by the author in the context of his work for ASFINAG.

Thanks to intelligent sensor data fusion it could be shown that the detection probability of events in road tunnels can be increased significantly while at the same time markedly reducing false positives.

The project was tested in three ASFINAG (Austrian Corporation for the Funding, Construction and Operation of the Country's High-Ranking Road Network) tunnels

1. BACKGROUND

As a result of the author's many years of membership in various working committees of "Österreichische(n) Forschungsgesellschaft Straße - Schiene - Verkehr FSV" (Austrian Research Society for Road, Rail and Traffic) as well as the fact that he had already had many years of experience with the operation of road tunnels at the time, the author recognised that the system architecture of operating and safety technology (Austrian acronym: BuS) in the tunnel systems harboured possible improvement potential. In principle, the sensor system architecture in road tunnels used to look as follows: [1]

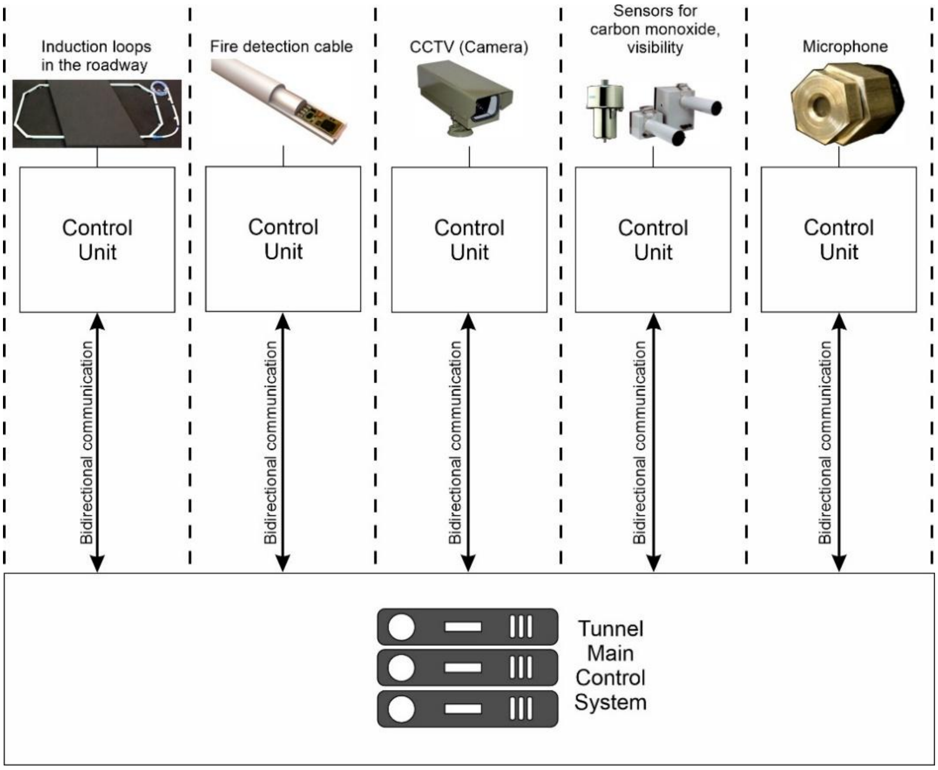

Figure 1: Principle of system architecture sensors in Austrian road tunnels

Every detection system is directly connected to the tunnel controls' central system (most often via a control unit) and is largely treated as independent from the adjacent systems. In reality, the technical realisation of the various sensor systems in Austrian road tunnels are vastly more complex. Especially data connection of the individual subsystems of a road tunnel's operating and safety equipment (BuS) and sensors is much more elaborate, meeting the current state of industrial standards. However, this doesn't change the parallel structure of the system architecture.

Each sensor works according to its technical/physical possibilities. This results in measuring errors whose deviation from the "correct" value vary. These measuring errors occasionally result in "false positives". The system architecture shown in Figure 1 has the disadvantage that systems' false positives add up and are transmitted to the SCADA system of the connected control centre. Following similar cases in the automotive industry, the author's idea was to combine various sensor systems' information on events in the tunnel to increase detection probability while lowering the rate of false positives. This idea led to the three-phase "Tunnel Sensor Fusion" R&D project [9]. The correct term is sensor data fusion. The principle is not new as it was used by NASA in its Apollo missions in the 1960s, back then using the Kalman filter to navigate its space ships ([2], Chapter 3.1, 3.1.1).

In the 1980s, the automotive industry started to use serially produced sensor data fusion to securely trigger certain systems in their vehicles [2]. Specifically to trigger airbags, [3], [4] and anti-lock brakes, [5]. Generally, one can describe sensor data fusion as follows: "Sensor fusion is defined as the process of combining signals acquired from various sensor sources to create a more valuable and precise output than that provided by individual sensors.…" [6]

2. R&D PROJECT TUNNEL SENSOR FUSION

Due to the novelty and complexity of this undertaking, the tunnel sensor fusion project was divided into three phases stretching several years.

2.1. Phase I

Feasibility study to determine the basic principle of a fusion of various sensor families in a road tunnel. This phase was done offline, meaning that real event notifications from the data base of a tunnel in operation were copied and fed into test algorithms in the office.

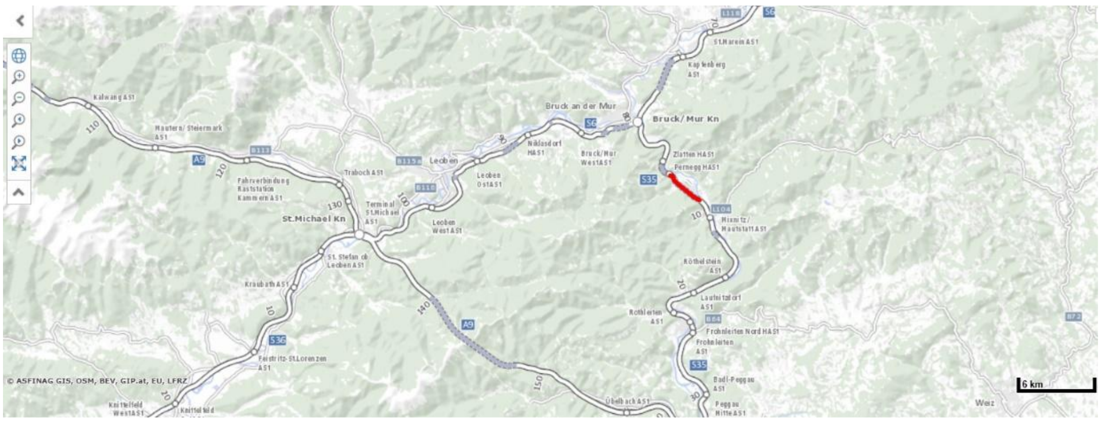

Figure 2: Screenshot ASFINAG GIS, S35 Expressway (Brucker Schnellstraße) with Kirchdorf Tunnel(red)

Kirchdorf Tunnel along the S35 Brucker Schnellstraße was chosen, specifically because it marked the first ASFINAG tunnel equipped with the then-new "Acoustic Tunnel Monitoring" (AKUT). [7]

Kirchdorf Tunnel is indicated in red in Figure 2. The tunnel has two tubes (one for every carriageway), is approx. 2.8 km long and was opened for traffic in May 2010. This tunnel's average daily traffic load in 2014 was approx. 16,400 vehicles.

At project start, no scope for the determination of the detection probability and simultaneous reduction in false positives had been defined. That's why the first, self-chosen task of the research consortium was an object-based data fusion (to model the tunnel). This, however, assumed that the installation position and physical/structural behaviour of every sensor ("sensor noise") had to be known exactly. Since this information was not available for the Kirchdorf Tunnel, the modelling approach was sidelined and the focus shifted to data fusion at property level (by means of machine learning). Basic information on artificial intelligence in general and machine learning in particular can be found in [8].

In preparation for tunnel sensor fusion, one important requirement is to create a "type of event/sensor" matrix as a first step. An extract of such a matrix for the Kirchdorf Tunnel is shown in the following.

Nr.	Detektierbare Ereignisse	Kurzzeichen	Aktuelle Sensorik																			Neue, innovative Sensorik				
			Trübsicht-messgerät	CO-Messgerät	NO_x-Messgerät	Längsströmungs-geschwindigkeits-messgerät	Brandmeldeanlage		Kontaktgeber						Einrichtung zur Komm. mit ÜZ	Verkehrserfassung	Verkehrsüberwachung	Leuchtdichtekamera	Videodetektion	Höhenkontrolle	Umweltdatenerfassung	AKUT	Automatische Gefahrguttransport-Überwachung	WIM-Sensor	Laserscanner	Infrarotkamera
			[1/10³ m]	[ppm]	[ppb]	[m/s]	automat. Brandmelder	Handgefahrenmelder (BRAND)	Handgefahrenmelder (SOS)	Notrufnische			Feuerlöschnische	Notausgang	Notrufnische	Induktivschleife / Überkopfsensor	Radar, Section control	[cd/m²]			Fahrbahnsensor	Akustisches Tunnel Monitoring				
			Messbereich: 0-15 m Messgenauigkeit: +/- 2%	Messbereich: 0-200 ppm Messgenauigkeit: +/- 2%	Messbereich: 0-500 ppb Messgenauigkeit: +/- 2%	Messbereich: +/- 15 m/s Messgenauigkeit: +/- 2%	Maximal- und Differentialwerte			Türkontakt NRN-Türe	Türkontakt Feuerlöschabteil	Entnahmekontakt Feuerlöscher	Türkontakt FLN-Türe	Türkontakt Notausgangstüre	Notrufeinrichtung in der NRN	- Anz. Pkw - Anz. Lkw - Geschw. - Stauerkennung		- Außenleuchtdichte - Leuchtdichte Einsichtstrecke - Leuchtdichte Durchfahrtsstrecke	- Stau - Fahrzeugstillstand - Falschfahrer - Langsamfahrer - Pannenbuchtbelegung - Rauch	Überhohe Fahrzeuge	- Nässe - Glätte	Unfall, Kollision	- Kfz-Kennzeichen - Art der Gefahrgüter nach UN Nummern - Inhaltsangabe (Menge)	Fahrzeuggewicht	Fahrzeugsilhouette	Temperatur von Fahrzeug und Ladung
1	Überhöhte / nicht angepasste Geschwindigkeit															x	x		x							
2	Hohe Verkehrsdichte / stockender Verkehr	VDE-03 / VBD-01														x			x							
3	Stau / Staugefahr	VDE-02 / VBD-02														x			x							
4	Langsames Fahrzeug	VBD-04														x			x							
5	Fahrzeugstillstand / Liegenbleiber	VDB-05																	x							
6	Belegung Pannenbucht	VDE-05														x			x							
7	Falschfahrer (Geisterfahrer) / Rückwärtsfahrer / Wendemanöver	VDE-04 / VBD-03																	x							
8	Fahrbahnfremde Gegenstände auf der Fahrbahn / Pannenbucht	VBD-09																	x							
9	Personen / Tiere auf der Fahrbahn	VBD-11						x	x	x				x					x							
10	Auslösung Höhenkontrolle	VDE-06																		x						
11	Glatte Fahrbahn																		x		x					
12	Unfall / Kollision	VBA-05													x				x			x				
13	Notruf	NRN-03 / NRN 04						x	x						x											
14	[illegible]	[illegible]																	x						x	x
15	Feuer / Fahrzeugbrand	VBD-07	x	x			x	x		x	x	x	x	x	x				x							x
16	[illegible]	[illegible]								x					x				x				x	x	x	
17	TS-Grenzwertwertüberschreitung / Sichteinschränkung, Trübung, Rauch	LQ-03 / VBD-06	x																x							
18	CO-Grenzwertüberschreitung	LQ-02		x																						
19	NOx-Grenzwertüberschreitung	LQ-04			x																					
20	Ausfall Lüftungsanlage	TL-01 / TL-02 / TL 03				x																				
21	Ausfall Beleuchtungsanlage	DFB-01 / EFB-05																x	x							
22	Ausfall Mittel- / Niederspannungsanlage	MSP-01 / MSP-02 / MSP 03 / MSP -04 / MSP-05 / MSP-06 / NSP 01 / NSP-02																	x							

Figure 3: Extract from an event-sensor matrix for the Kirchdorf Tunnel

15	Feuer / Fahrzeugbrand	VBD-07	x	x			x	x		x	x

Figure 4: Event sensor-matrix zoom, Figure 3

Figure 3 shows possible events in a road tunnel from top to bottom and the sensor systems installed in the Kirchdorf Tunnel from left to right. An X in a cell means that the event listed in the row can be detected automatically by the respective sensor system in the Kirchdorf Tunnel. If a row contains more than one X this event can be detected by different sensor systems, meaning that all these various sensors can be combined using suitable algorithms. For a better view, the row containing the event type "fire / vehicle fire" was enlarged and displayed as Figure 4.

The general idea is in the assumption that one event type (e.g. drivers going the wrong way) in the tunnel is detected by several sensors belonging to various sensor families at various points in the tunnel. This results in the so-called feature vector. $x \in \mathbb{R}^n$:

$x = [WrongWayDriverCounter, SlowVehicleCount, SmokeCount, StoppedCount]^T$

In the feature vector, the viewed events are listed with one index number each. A feature vector of $x = [2,3,0,0]^T$, for instance, means that the involved sensor systems have detected the (same) wrong-way driver twice and a slow-moving vehicle three times in the same time window. The detection of slow-moving vehicles could originate from several, different vehicles and are most likely a secondary response to the wrong-way driver.

The detected feature vectors are then categorised using classification algorithms.

In the case of the wrong-way driver event type, the measurement results of the video detection and induction loop sensor families were combined using the sensor data fusion algorithm.

Training and test set for event type *Wrong-way driver*

Table 1: Overview of test data for the wrong-way driver event type

Set	**Number of Labels**	**True Positive Labels**	**False Positive Labels**
Total Set	169	166	3
Training Set	101	99	2
Test Set	68	67	1

The term label in Table 1 refers to the label assigned to a data set. Each data set was evaluated by a person and labelled accordingly based on the respective event video.

In machine learning, it is necessary to train the algorithm with (verified) test data. Table 1 shows the amount of data sets of the wrong-way driver event type that was used to train and test the respective algorithm.

A label contains:
- Time and date
- Class
- True positive or false positive

The assessment on the likelihood of event type X based on the present feature vector was carried out using widely available, tried and tested as well as documented classification algorithms. Various algorithms were tested to determine the best suited one. A description of the classifiers can be found in [9]. A comparison of the software-technical implementation of the classifier algorithms using "scikit-learn" can be seen in [10].

Table 2: Performance of different classifiers, wrong-way driver, Kirchdorf Tunnel

Classification algorithm	**Detection performance**
Nearest neighbour	0.985294117647
Linear Support Vector Machine (SVM)	0.985294117647
Linear Discriminant Analysis (LDA)	0.985294117647
Decision Tree	0.970588235294
Random Forest	0.970588235294
AdaBoost	0.985294117647
Radial Basis Function Kernel (RBF) SVM	0.985294117647
Naive Bayes	0.970588235294

The results of the probabilities for the wrong-way driver event type computed using various classifiers are shown in the right-hand column of Table 2. 1.0 equals 100% correct.

It is evident that several classifiers detect the wrong-way driver event type with a probability of > 98.5%

The approach within the project as well as all detailed events are listed in [11].

2.2. Phase II

Live system mounted in a road tunnel in operation; A (virtual) server on which various classifiers were tested was set up in parallel to the tunnel head server. See Table 3. The virtual server's software picked event notifications up from the tunnel head server, processed them in the sense of sensor fusion and entered the result into a data base together with the raw data from the individual sensor families for comparison. It did not interfere with the tunnel controls. Fears that the test system would be overloaded by the flood of data were unfounded.

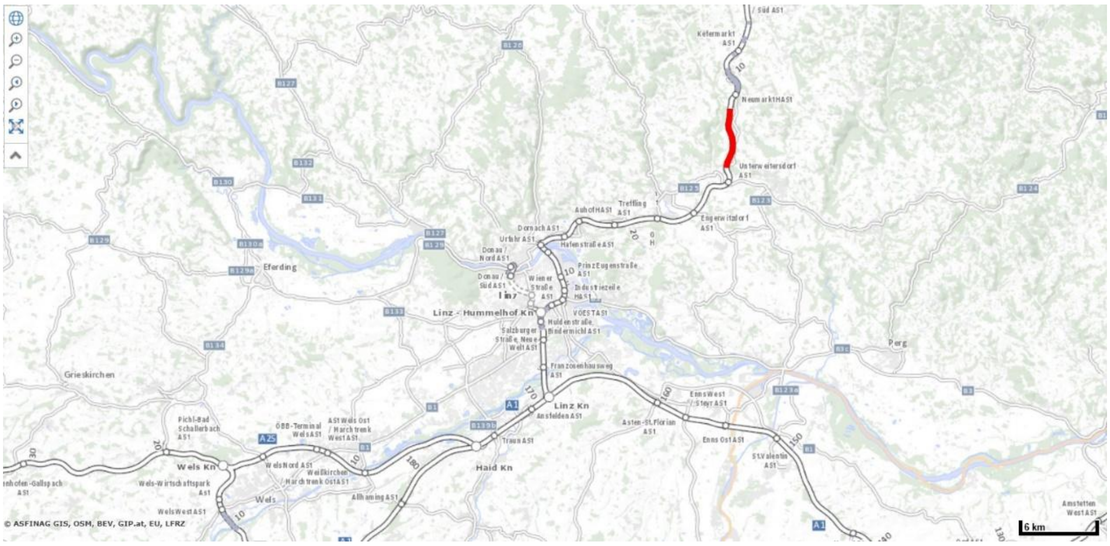

Figure 5: Screenshot ASFINAG GIS, S10 Expressway (Mühlviertler Schnellstraße) with Götschka Tunnel (red)

As a test object, the then-newest ASFINAG tunnel, the Götschka Tunnel along the S10 Mühlviertler Schnellstraße was chosen. The Götschka Tunnel is approx. 4.4km long, has two tubes (unidirectional traffic in each) and is equipped with combined ventilation (partially longitudinal, partially semi-transversal). Additionally, the Götschka Tunnel is equipped with "Acoustic Tunnel Monitoring" (AKUT). This fact was also relevant to the selection of this tunnel as a test object as this sensor type is also installed in the Kirchdorf Tunnel (Phase I), meaning that its configuration was very similar. In the project year of 2017, the average northbound traffic came in at approx. 18,000 vehicles, southbound at approx. 24,000 vehicles.

Results of sensor fusion using the example of the *wrong-way driver* event type.

Table 3: Performance of different classifiers, wrong-way driver, Götschka Tunnel

Classification algorithm	**Detection performance**
Nearest neighbour	0.848648648649
Linear SVM	0.848648648649
RBF SVM	0.816216216216
Decision Tree	0.816216216216

Random Forest	0.837837837838
AdaBoost	0.854054054054
Naive Bayes	0.383783783784
LDA	0.848648648649
dummyMostFrequClass	0.627027027027
dummyStratified	0.6
dummyUniformPrediction	0.540540540541

The results of the probabilities computed for the wrong-way driver event type based on various classifiers are shown in the right-hand column of Table 3. 1.0 equals 100% correct.

With the wrong-way driver event type the AdaBoost classifier reached its highest probability of > 85.4%.

Analysis and interpretation of Phases I and II

Both the Kirchdorf Tunnel and the Götschka Tunnel are tunnels of Risk Class III. This means that their equipment meets the same standard RVS requirements.

Nevertheless there are differences within the same classifiers which were tested for the wrong-way driver event type. Comparing the results of the classifiers in table 2 (Kirchdorf Tunnel) with the results of table 3 (Götschka Tunnel), it is evident that the results in the Götschka tunnel are consistently smaller for the same classifiers.

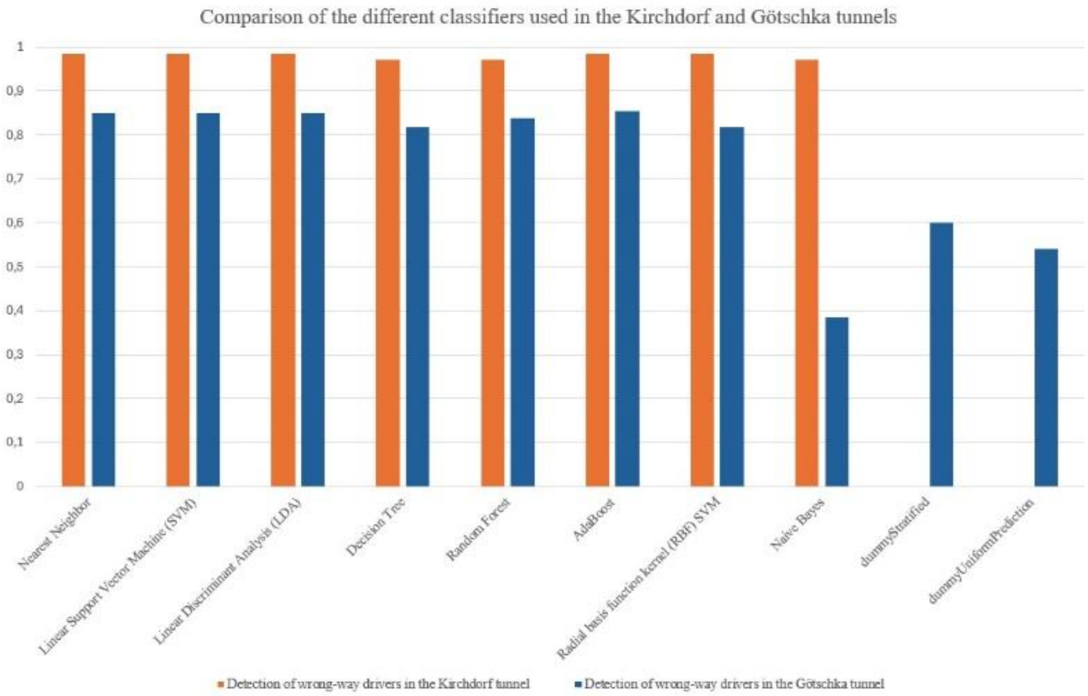

Figure 6: Diagram Comparison of the performance of different classifiers in the Kirchdorf / Götschka Tunnels

The differences in the performance of the algorithms were not looked at in detail in the framework of this project, but should be investigated in detail for all tunnels if one seeks to find a standard solution for the future. One possible explanation lies in the different tunnel cross-sections of the Prag-bound tube of the Götschka Tunnel which has three lanes instead of the two lanes of the Linz-bound / both tubes of the Kirchdorf Tunnel. One reason for this could be that video detection, which contributes significantly to sensor data fusion, is (negatively) affected by the changes in tunnel geometry.

Both in Phase I and Phase II the AdaBoost classifier reached the highest detection probability.

2.3. Phase III

The aim of this project phase was to install a live system at an operational road tunnel and to present the results of the sensor data fusion in the responsible "regional traffic management centre" (rVMZ) of ASFINAG..

The focus of Phase III was less on checking the performance of classifiers / sensor fusion itself but more on making the results of sensor fusion available to the operators of the monitoring Regional Traffic Management Centre (rVMZ). The results of the sensor data fusion algorithm were displayed to the rVMZ's operators in addition to the conventional control technology (SCADA system). Using a specifically designed graphic interface, the operators were able to evaluate the correctness of the sensor data fusion algorithm once an event was processed. The system did not interfer with the tunnel controls or the rVMZ's control technology. The additional work for the operators in evaluating the results of the sensor fusion algorithm for its correctness yielded some highly valuable insights! The result: Many false positives were filtered out and all real alarms were displayed as such.

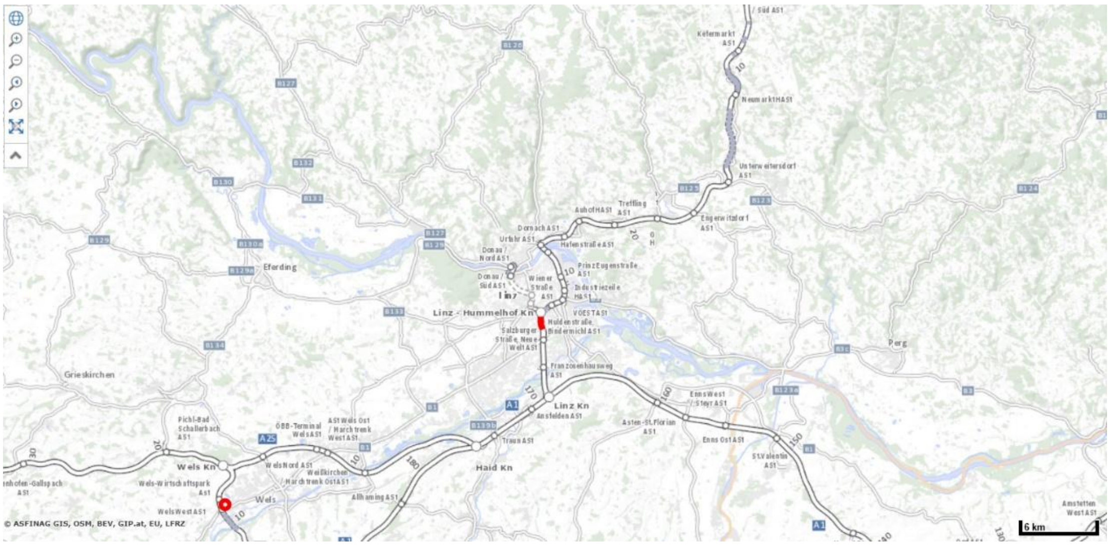

Figure 7: Screenshot ASFINAG GIS, A07 Highway (Mühlkreis Autobahn) with Bindermichl Tunnel (red)

The Bindermichl Tunnel along the A07 motorway (Mühlkreisautobahn) was chosen as a test object for Phase III. Many events occur in the Bindermichl Tunnel, which is very important for testing this novel system.

The Bindermichl Tunnel is an urban structure (rectangular cross-section) 1.06 kilometres long. It consists of two tubes with several lanes each as well as complex geometry with several accesses and exits. The tunnel has a north-south orientation and a daily average traffic volume of approx. 95,000 vehicles in the project year of 2023.

The Wels Regional Traffic Management Centre (rVMZ) is responsible for monitoring the tunnel.

Just like Phases I and II of the project, various classification algorithms were tested to determine the best-suited one.

The following classifiers were tested:

Table 4: Classification algorithms tested in the Bindermichl Tunnel

Nearest neighbour
K-Nearest neighbour
Logistic Regression
NG-Boost
XG-Boost
Decision Tree
Random Forest
Support Vector Machines

The analysis of the results data [12] showed that the NG-Boost classifier is best suited for this application.

“NGBoost generalizes gradient boosting to probabilistic regression by treating the parameters of the conditional distribution as targets for a multiparameter boosting algorithm. Furthermore, we show how the Natural Gradient is required to correct the training dynamics of our multiparameter boosting approach. NGBoost can be used with any base learner, any family of distributions with continuous parameters, and any scoring rule. NGBoost matches or exceeds the performance of existing methods for probabilistic prediction while offering additional benefits in flexibility, scalability, and usability.” [13]

The good result of the NGBoost algorithm confirms the performance of the Ada-Boost classifier in Phases I and II. It appears that the "boost" algorithm family is suited for the application of detecting events via tunnel sensor fusion.

Sensor data fusion results using the example of the *wrong-way driver* event type
Result of the (event video) evaluation by one person (data set "labelling", see Phase I) - all event types,
Test period 12.11.2023 to 11.01.2024

Table 5: Result evaluation by event videos, Bindermichl Tunnel

	Quantity
False events revealed by video analysis	648
True events revealed by video analysis	669
Total	1317

Algorithm results - all event types, test period 12.11.2023 to 11.01.2024

Table 6: Result of the algorithm, Bindermichl Tunnel

	Quantity
False events according to algorithm	648
True events according to algorithm	654
Exceptional special cases	15
Total	1317

In the test period of 12.11.2023 to 11.01.2024, the sensor fusion algorithm was able to compute 648 false positives as false in the Bindermichl Tunnel! All true alarms were correctly detected! The true alarms were displayed on the rVMZ test system's monitor and stored in a data base. Events detected as special cases were classified by a person based on event videos and showed certain deviations from common events. Example: Vehicle stopped on the hard shoulder - the (usual) "stopped vehicle" event refers to a driving lane. Classified special cases: Reflection from wet roadway; snow on the roadway; stationary vehicles, triggered by the exit ramps. Although the special cases were identified and annotated by one person, they were not discussed further in this project.

3. SUMMARY AND CONCLUSION

The project showed that superpositioning the detection results of various sensor systems for one event type yields significant increases in detection probability while simultaneously lowering false positives. It is recommended to further pursue the principle of tunnel sensor fusion.
However, the following aspects should be investigated in follow-up projects:

- Test in tunnels with bidirectional traffic: All listed project phases were carried out in unidirectional tunnels (one tube per direction).
- Test which combination of sensor families suitable for an event type is optimal: Parameters of detection time, detection probability
- Direct access to the tunnel's subsystems. Collection of raw sensor data to prevent inadvertently neglecting the acknowledgement of past events (according to the system architecture for Austrian road tunnels)
- Consideration of roadway reflection
- Consideration of special tunnel geometries (access/exit ramps) and their effects on various event types
- Investigate the influence of tunnel geometries (number of lanes, round/rectangular cross-section, with/without false ceiling) on the important sensor family "automated video detection"
- Test how low the detection performance of individual sensor families may drop without negatively influencing the tunnel sensor fusion's overall performance
- What technologies are optimal for the individual sensor systems in making the best possible contribution to tunnel sensor fusion?
- Is it possible to optimate event detection time through (early) incorporation of unusual circumstances in the tunnel detected by tunnel sensor fusion?

One important insight is that the method shown here works in different tunnels that remain one-offs despite technical standardisation.
Classifiers from the family of boost algorithms appear to offer benefits over other classification algorithms for this application in terms of probability

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4.2. Figures

4.3. Tables