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Data driven degradation of automotive sensors and effect analysis

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Abstract

Autonomous driving plays a crucial role to prevent accidents and modern vehicles are equipped with multimodal sensor systems and AI-driven perception and sensor fusion. These features are however not stable during a vehicle's lifetime due to various means of degradation. This introduces an inherent, yet unaddressed risk: once vehicles are in the field, their individual exposure to environmental effects lead to unpredictable behavior. The goal of this paper is to raise awareness of automotive sensor degradation. Various effects exist, which in combination may have a severe impact on the AI-based processing and ultimately on the customer domain. Failure mode and effects analysis (FMEA) type approaches are used to structure a complete coverage of relevant automotive degradation effects. Sensors include cameras, RADARs, LiDARs and other modalities, both outside and in-cabin. Sensor robustness alone is a well-known topic which is addressed by DV/PV. However, this is not sufficient and various degradations will be looked at which go significantly beyond currently tested environmental stress scenarios. In addition, the combination of sensor degradation and its impact on AI processing is identified as a validation gap. An outlook to future analysis and ways to detect relevant sensor degradations is also presented.

Problem Statement and Awareness

Vision Zero

The number of road fatalities remains high. According to [3] a person dies on public roads every 23s approximately, leading to around 4000 fatalities every day. In some regions, the numbers seem to converge, however to a level significantly above zero. In other regions, the number of fatalities are rising as shown in Fig. 1. It is fair to say that *Vision Zero* [6] is still far away.

Innovations

Major ADAS innovations (see [1] over the last decades have significantly helped reduce road fatalities. These innovations also include the introduction of advanced chassis and crash tests in the 1950s, mandatory seat belts in the 1970s, airbags in the 1980s and so on. Euro NCAP also introduced electronic stability control (ESC) in 2011 and automatic emergency braking (AEB) in 2014 within the safety ratings. AD challenges are described in [2, 8, 14, 20].

1. sensors The latest generations of sensors with readout noise below 1 e^- and raised Quantum Efficiency (QE) curves within the infrared spectrum (for actively illuminated applications, e.g., in-cabin) are examples where technical limits are almost reached. Similar effects apply for other modalities (radar, LiDAR, ...). Additionally, e.g., high resolution solid state LiDAR are introduced. A comprehensive overview is provided in [17].

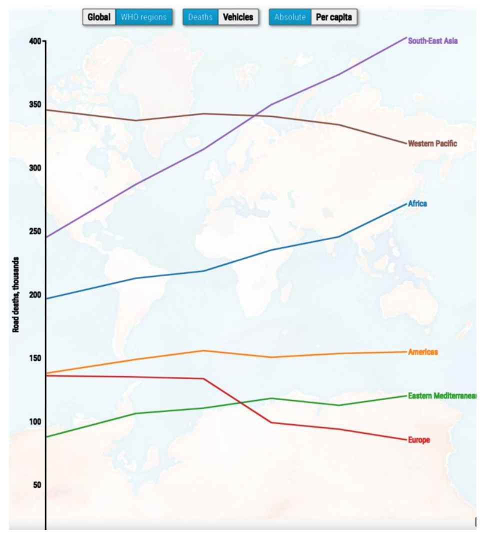

Figure 1. Deaths on the road based on WHO 2018 report, from [3]

2. AI On algorithmic level, AI driven approaches have boosted detection and classification capabilities, sometimes even leading to superhuman performances. The tremendous development effort on component and system level get closer and closer to current technological limit.

3. standardization Standardization like IEEE P2020 [7, 13] activities are crucial in objectively quantifying automotive image quality performance. Assessing the sensor stream in an algorithm- and vendor-agnostic way helps in objectively ensuring that the sensor stream contains appropriate contrast/information so the subsequent AI units have a chance to perform classification. As stated in IEEE P2020 context by one of the authors, ”IQ (image quality) can decide of being dead or alive” [4].

Blind Spots: Sensor Degradation

Despite huge dedication in system design, once a vehicle is released into the field, it is mainly left to itself, leading to the following blind spot: ADAS and AD systems fundamentally rely on the robustness and trustworthiness of the underlying sensor systems and components. Even with state of the art safety features found on modern vehicles, the inherent risk of sensor degradation remains unaddressed which poses a risk for vehicle passengers as well as vulnerable road users (VRUs). AI and deep learning disrupt the severity even more since they are especially receptive to sensor degradation effects because of their nonlinear nature.

Why is sensor degradation relevant?

Fig. 2 shows a generic ADAS pipeline with sensor space, feature space and function/action space. Sensor degradations lead to biased, altered or reduced information which may lead to unexpected malfunction of the resulting ADAS system(s). For AEB this can result in increased false negative rate (braking too late / not at all) and/or increased false positive rate (false alarm braking).

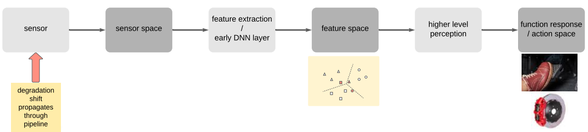

Figure 2. *Generic ADAS/AD system pipeline. Biased input due to degraded sensors and its propagation leading to system malfunction.*

Which sensor degradation effects are relevant?

Not all sensor degradation effects are necessarily relevant in the customer function domain. Instead of focusing on the sensor domain, we are proposing to concentrate on the resulting customer domain. Obviously, this is strongly dependent on the rest of the pipeline of the imaging system. Similarly to MP3 for audio, if a certain effect (e.g., color shift of color filter array of a camera) does not impact the resulting ADAS/AD function, it can be ignored. Some minor degradations however may be surprisingly relevant to small changes (e.g, certain scratches in a windshield) if the downstream ADAS/AD processing heavily relies on certain image quality properties.

Related Work – What is done today and why it is not enough

Where is PTI for Sensor and ADAS/AD system degradations?

Periodic technical inspection (PTI) covers major mechanical degradations (e.g., brakes) however it is not addressing sensor degradations or resulting system level degradations yet.

sensor domain vs. function domain

To the best of our knowledge, existing work focus on the sensor domain only. The link between the sensor domain and the function domain can be overlooked. Only when sensor degradations are seen to have an effect on the function domain, are they classified as relevant. Further analysis is purely concentrating on detecting such degradations alone. However, the link back to the function is not evaluated systematically.

FTA – What sensor degradations can happen?

In the industry where multi-dimensional and largely complex systems are used, structured methods were established decades ago to ensure coverage of the problem (and solution) space. In this study, we are proposing a structured approach around possible failure causes. Their effect is only quantifiable in limited cases. Mapping these potential failure causes together leads to a structured fault tree analysis (FTA). Fig. 4 generically depicts the overall fault tree analysis (FTA) of ADAS and AD systems. The intense current effort in development focuses on the right branch of this tree – leading to various innovations that improve safety. Detection/classification systems have been hugely improved by the rise of AI in automotive for example, leading especially to lower false negative rates. Sensor modality mismatch has also benefited from the latest sensor technologies. And so have extended functional safety (FuSa — ISO26262) and safety of the intended functionality (SOTIF — ISO21448). The left branch of the tree in Fig. 4 shows possible identified gaps: if relevant sensor degradations are present and the onboard self diagnostic system (e.g., blockage detection, online calibration self-diagnostics) generates false negatives (i.e., sees sensor stream as fit), degraded sensor inputs are fed into the ADAS pipeline without recognition. This can lead to an overall failure of the intended functionality.

FTA for sensor calibration degradation

Fig. 4 shows the fault tree in the context of sensor calibration. Different calibration factors can impact the overall ADAS system level performance. Most state of the art systems with high accuracy requirements (this is the case for all current ADAS and AD systems) can lead to wrong detection angles or wrong intrinsic calibration data. An incorrect (e.g., outdated) intrinsic calibration uses parameters which are fed into the camera model of the processing pipeline. The intrinsic data can be impacted by specifics of the sensor (e.g. camera itself) and correspond to geometric changes inside the sensor path (e.g. optical path). The extrinsic calibration can be highly impacted if data are either not up to date or simply incorrect. When a sensor is replaced/removed following a repair or windshield replacement, the location of the sensor relative to the vehicle coordinate system is crucial. This is the main focus of this initial analysis since it can lead to severe impacts on the ADAS system. Deviations of several degrees (e.g. $\pm 3^\circ$) are possible. Calibration routines are often accompanied by a self check - the self-diagnostic. However the self-diagnostic has several limitations and only performs simple plausibility analysis which can be fooled either intentionally or randomly. If a sensor is changed after a repair event, then it is possible to install the sensor (and calibration target if applicable) in such a way that the system believes it is successfully calibrated although it is not. We call this *good versus successful* calibration. Successful means that the sensor is calibrated and all features are enabled but we do not know how good the 'quality of the calibration' is, i.e. what the calibrated values are against real world values. In the case of a good calibration, the calibrated values correspond to the real world data (or the error bars are within system acceptable boundaries). Typical values are in the range of $\pm 0.2^\circ$ or below.

FMEA approach for sensor degradations

To ensure full coverage of relevant sensor degradations, a Failure Mode and Effects Analysis (FMEA) like approach is proposed. Different technological modalities are mapped to partially overlapping failure classes. The following table illustrates a non-exhaustive mapping of relevant key components per sensor modality/system. State of the art ADAS or AD systems use

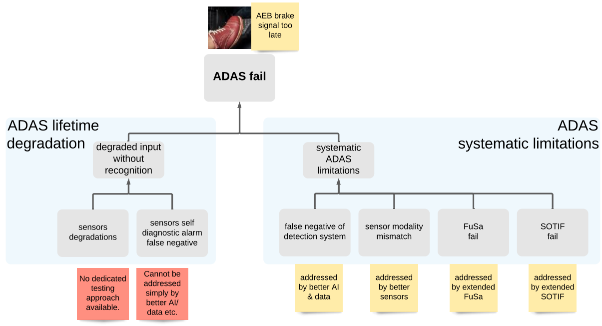

Figure 3. *Fault Tree Analysis (FTA):* ***Left:*** *Identified gap and focus.* ***Right:*** *Focus of traditional development.*

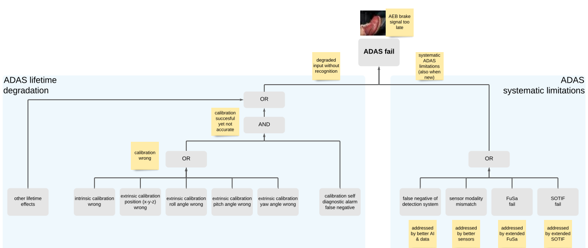

Figure 4. *Fault Tree Analysis (FTA) in sensor calibration context:* ***Left:*** *Identified gap and focus.* ***Right:*** *Traditional development focus.*

different sensor modalities, including cameras, RADARs and LiDARs. Degradation examples on camera sensor level alone are described in [10]. Current sensors also have a blockage/soiling detection [19]. This is similar to self-diagnostics systems and can be easy to trick and usually only determine severe blockages. In [18] this is discussed further for a LiDAR sensor.

Vehicle Lifecycle Journey – Sensor degradation analysis

The industry performs several activities already today to ensure sensors perform according to the specification. However, the main focus remains with the development cycles. The so-called DV/PV (design validation and process validation) are used to develop robust sensors. During exhaustive tests, the lifetime of a vehicle is simulated for a small number of samples. However, these tests lack the interaction at system level as well as the interaction between the software (detectors, path planning) and the sensors. A true end-to-end analysis cannot be performed this way. Moreover, AI triggers risks since sensors can react non-continuously to small sensor inputs ("butterfly effect"). This especially holds if AI is fed with biased sensor data over lifetime while AI training was performed with new sensors only. Thus, the AI systems sees sensor data from a different (compromised) area in data domain. Real world effects on a large scale (e.g. miscalibration after sensor removal/replacement) and their impact on the system level performance are currently not covered systematically.

Sensor Degradation – What could go wrong on sensor level (input)?

Several faults can happen at sensor-level. An overview of such faults on camera level and their effects on AD can be found in Secci et al. [16]. The effects can be categorized into the following 2 items:

- sensor geometric degradations (e.g., miscalibration)
- sensor signal degradations (e.g., color shift of CFA)

Miscalibration can be triggered by several effects such as:

- wrongly replaced or installed sensor (e.g. after a windshield repair)
- change in the vehicle itself (e.g. after an accident or part movement due to deformation of the vehicle over lifetime)
- aging of sensor holder(s) or bracket(s)
- failures in the storing of new calibration data (e.g. electrical faults)
- mismatch of online calibration with professionally performed calibration (either at OEM end-of-line or after professional replacement of a part/sensor)
- and several more

However the main challenge remains that the real effect on the system level performance and behavior is unclear. Ultimately the effect is relevant if (and only if) a degradation or impact on the final stage (customer or vehicle domain) is noticeable. In the case of an AEB system, that could manifest as a a false alarm being triggered or a braking signal generated too late or missed completely due to a miscalibrated system for example.

AI Sensitivity – Adversarial attacks

Recent publications show that it is possible to *trick* AI systems [21, 15, 12] by minor changes in sensor domain. Systematically we have four cases on risks as shown in 5. Especially the cases where unknowns are involved (adversarial risk and open class risk) are specifically challenging to handle.

KPI proposal

Degradation KPIs - macroscopic

A KPI (key performance indicator) driven approach is proposed. It is crucial to formally define KPIs by which sensor and system degradation are measurable. In automotive imaging, IEEE P2020 [13, 7] plays a key role for image quality of camera systems. At macroscopic level, a degradation can be assessed within the shift of the receiver operating characteristics (ROC) curve as depicted in Fig. 6 on macroscopic level. For degradation $\Delta(\mathcal{C}) = A - A'$ it holds:

description	front view camera	RVC / SVS Kamera	Lanewatch camera	in cabin monitoring	nightvision	LIDAR	Ultrasonics	Radar	Dashcam	inside smart mirror	outside smart mirror
extrinsics	x	x	x	x	x	x	x	x	x	x	x
windshield/backlight	x				x					x	
protection flap		x								x	
active illimination				x	x	x					
lens	x	x	x	x	x	x			x	x	x
lens holder	x	x	x	x	x				x	x	x
sensor	x	x	x	x	x	x			x	x	x
ISP	x	x	x	x	x				x	x	x
pcb	x	x	x	x	x	x		x	x	x	x
processing unit	x	x	x	x	x	x		x		x	x
PHY		x	x	x	x	x	x	x	x	x	x
connector		x	x		x	x	x	x	x	x	
cable		x	x		x	x	x	x	x	x	
image processing unit		x	x		x				x	x	
display controller		x	x		x				x	x	x
display		x	x		x				x	x	x
cleaning units	x	x	x		x	x		x	x	x	
accoustic warning	x	x	x	x	x					x	
overlay or signal lamp	x	x	x	x	x					x	

FTA table: How are key ADAS/AD components potentially affected for different AD sensor modalities along the processing pipeline.

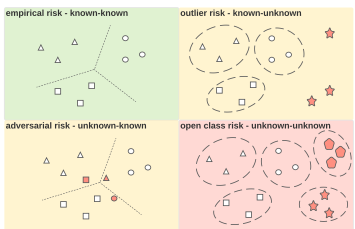

Figure 5. *The four quadrants of risks from [21]. A biased sensor stream might lead to areas in feature space with low or no sampling coverage.*

$$\int_\lambda TPR(\lambda)\overbrace{FPR'(\lambda)\,\mathrm{d}\lambda}^{\mathrm{d}FPR}$$

$$\int_\lambda \mathcal{C}(TPR(\lambda)FPR'(\lambda))\,\mathrm{d}\lambda$$

$$\delta(\mathcal{C})_\lambda = TPR(\lambda) - \mathcal{C}(TPR(\lambda))$$

At microscopic level, the impact of degradations is assessed for a specific working point on the ROC curve. Fundamentally, this leads to a derivative of function KPIs (e.g., TP/FP rate) wrt. sensor degradation KPIs (sensor domain).

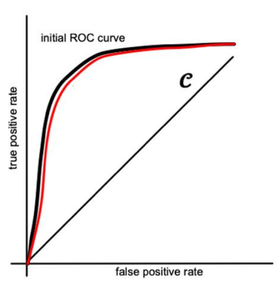

Figure 6. *Receiver Operating Characteristics (ROC) curve and the qualitative impact of sensor system degradation.*

Additional degradation KPIs - microscopic

Additional microscopic KPIs are also proposed. They can help quantify the effect of degradations such as as a camera miscalibration. Proposed KPIs:

- **number of first detected frame** – the first frame where the detector *sees* an object - this can be used to compare ground truth with affected sensor stream
- **number of missed frames** – how many frames are missed by the detector between ground truth and affected sensor data stream
- **number of frames with high confidence** – sequence of frames in which the confidence level of the detector input is above a certain threshold where ground truth and affected sensor stream is compared
- **distance estimation** – sensor degradation, especially in the case of a miscalibrated sensor, can lead to a misinterpretation of the distance to certain objects. This is especially true for 2D sensors such as cameras.
- **detection confidence delta** – delta in detection confidence for a sequence of frames between ground truth and affected sensor

Additional KPIs can also be introduced depending on the scene. This way the *real* effect of a degradation mechanism through the entire processing pipeline can be understood.

Degradation analysis setup
Motivation

Intrinsic and extrinsic calibrations are preformed at certain moments within the vehicle lifecycle. An intrinsic calibration is executed during the production of the sensor and typically assumed as invariant against environmental changes despite the fact that the lens map of a camera varies with temperature and thus the mapping of view ray angles to pixels is not constant. Extrinsic calibrations are typically performed during the production of the vehicle at the end-of-line and repeated when relevant components are replaced (e.g., sensors, windshield). In addition, some sensor systems allow for target-less online calibration mechanisms to update its extrinsic sensor calibration data. The remaining risk is that a calibration routine may be conducted successfully, but the actual calibration data in itself is not accurate (Fig. 7). For target based extrinsic calibrations, this could be present for example when the underlying assumptions of accurate target placements are not fulfilled (as sensor to vehicle is calibrated transitively by ”sensor to target” and ”target to vehicle”.

In this initial analysis we focus on effects which are linked to extrinsic calibration challenges. An extrinsic calibration is used to determine the orientation and position of a sensor into the overall

calibration matrix - self diagnosis vs. reality	
"calibration succesful" + correct calibration -> OK	**"calibration succesful" + incorrect calibration** -> risk -> This POC
"calibration fail" + correct calibration (too sensitive self-diagnosis) -> not in scope	"calibration fail" + incorrect calibration result -> OK

Figure 7. *Calibration matrix – self diagnosis vs. reality. The risk remains that a succesful calibration is not automatically accurate.*

vehicle coordinate system. This is required for every sensor. SAE level 4+ based systems require re-calibration on a daily basis [11].

Hence, we propose the following setup:

Setup overview

SIL architecture overview

Fig. 8 depicts the proposed software in the loop (SIL) approach which allows for a structured comparison.

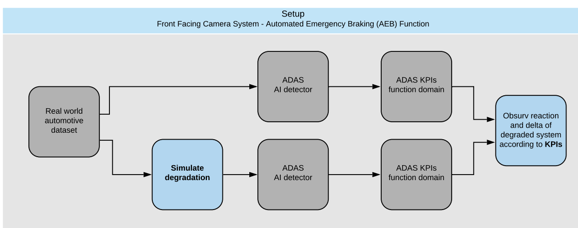

Figure 8. *SIL setup.* ***Top:*** *Original pipeline.* ***Bottom:*** *Simulated degradation pipeline.* ***Right:*** *KPI driven effect analysis.*

Realworld automotive sensor capturing setup

To ensure relevance for our automotive analysis, real world sensor data was essential. To this end, a Tesla Model 3 (MY2020, FSD3, sensor setup see [5]) was chosen where data from 4 of its cameras (front, 2x side rear and rear) was captured over a 12 months period. This produced a representative dataset including all typical environmental changes and combinations thereof (sunlight, lowlight, rain, snow).

Detectors

Various detectors for object detection were evaluated, including YOLO v3 and YOLO v4. YOLO serves as de facto standard of efficient yet high performance detectors. As shown by Bochkovskiy et al. [9] and illustrated in Fig. 9, YOLO v4 is seen as an extremely fast yet accurate state of the art object detector for automotive embedded processing.

Although our framework is detector-agnostic, we did choose such a state of the art detector (YOLO v4) as it is not limiting the end-to-end pipeline. A resulting degradation on system level is therefore not due to a specific limitation of an imperfect detector but rather a fundamental result of sensor degradation.

Initial Results

As discussed previously an extrinsic calibration can trigger several failure modes. In this study, we performed several real world tests to link possible failures to the relevant classes and KPIs. The categories we found were:

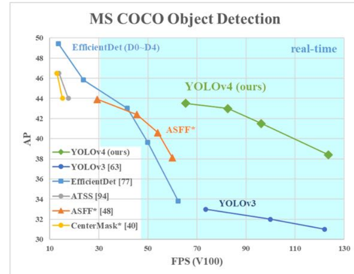

Figure 9. *Average precision (AP) of various object detectors based on MS COCO. YOLO v4 seen as superior detector that becomes relevant for real-time automotive embedded computing (from [9])*

- distance estimation faults — wrong pitch angle of the calibrated sensor can lead to errors in time to collision (TTC) estimation. That's because the TTC is based on distance estimation. This is especially true for 2D sensors such as cameras where a 3D distance estimation is not possible.
- trajectory planning — wrong roll or yaw angle can lead to possible collision being analyzed/detected too late.
- missed objects – calibration is often combined with ROIs inside the image to limit detection areas according to relevant crash and safety test scenarios. Applying wrong ROIs can lead to missed objects.
- impact on detector – calibration faults can trigger thresholds changes and impact the highly complex training approach on the detectors themselves and can lead to different detection performances.

In the study different angular errors of up to $\pm 3.0°$ were used for each *Euler*-angle analyzed. The following real world data illustrate the impact of the angular errors (see Fig. 10, 11, 12, 13, 14).

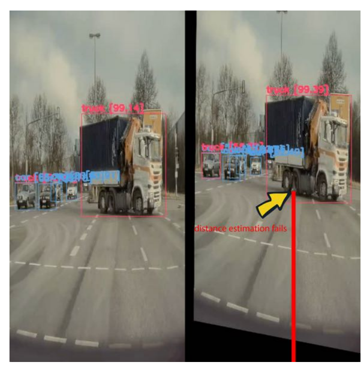

Figure 10. ***(left image)*** *Truck as seen by the ego-vehicle front camera (ground truth). The Truck shown is in the driving path of the ego-vehicle.* ***(Right image)*** *a wrong camera calibration is applied which is still potentially seen as "successful" by the system itself. This could lead to an emergency braking event triggered too late where an accident cannot be prevented.*

Results conclusion

Our preliminary systematic analysis can show expected behavior on real world data. A sensitivity driven analysis also shows that these effects can lead to systematic faults in the active safety

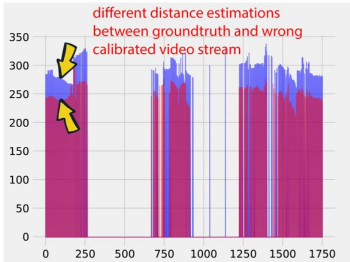

Figure 11. *The corresponding KPI plot shows the y-coordinate of the truck detected as a function of the frame number. The blue and red curves correspond to the left and right images and show how the y-coordinate is clearly different for the miscalibrated camera (which corresponds directly to an incorrect distance estimation).*

Figure 12. *This is another example of how the Time To Collision (TTC) could be mislead for a VRU in a real world example.*

Figure 13. ***(left image)*** *Pedestrian detected by the ego-vehicle front camera (ground truth).* ***(Right image)*** *A wrong camera calibration is applied (yaw and roll angle) which is still seen as "successful" by the system. The pedestrian is not detected by the miscalibrated device. Even if detected - the trajectory itself could be estimated and forecasted such that a possible collision is detected too late.*

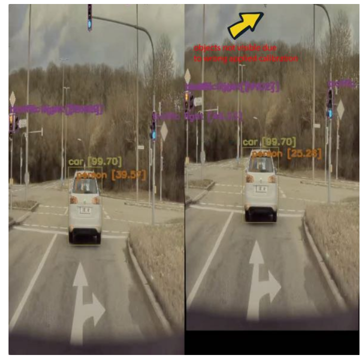

Figure 14. *Wrong calibration can also exclude objects as can be seen in this example. Extended ROI (region of interests) which are often used to exclude certain areas from the detectors can prevent detections from happening.*

or autonomous driving system. The framework of a software-in-the-loop approach enables a systematic analysis which can be then extended to analyze other more complex effects to create a mapping between input (sensor) domain and customer domain (e.g. a true positive detection or even a braking signal).

Conclusion & Outlook

In this overview paper it has been shown that lifetime effects can have significant impacts on the overall system level performance for ADAS and AD systems. The main challenge is that these effects are only relevant on the output domain (or customer domain) which correspond to driving and decision making signals whereas sensor effects act on the input domain. Artificial intelligence algorithms such as deep learning can also increase the overall complexity. As vehicle safety technology becomes ever more complex, the need for good extrinsic calibration of sensors after a repair or windshield replacement has grown. The correct functionality of the ADAS is dependent on it. While it is relatively easy to complete a successful calibration with the right tools, if not carried out correctly the on-vehicle software can wrongly determine the vehicle related parameters. As shown here with our sensor-in-the loop approach, a successful calibration could potentially result in the ADAS system not functioning as expected which could result in collisions with vulnereable road users. Further research will be carried out to systematically analyze the impact of sensor signal degradation. In addition, real world tests on vehicle level are planned to map the effect of sensor degradation to relevant test scenarios.

Acknowledgments

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Author Biography

Sven Fleck received his MS and PhD in computer science from the University of Tuebingen. With SmartSurv, he serves as reviewer, advisor and consultant in automotive and surveillance imaging domain for 15+ years where he mainly covers the OEM perspective to ensure best in class image/imaging quality, both for ADAS/AD and incabin. He is co-founder and vice chair of IEEE P2020 Automotive Image Quality Standardization working group to address the IQ KPI gaps. He serves as expert reviewer to the European Commission. Sven is co-founder and management partner of obsurver to address the gap of sensor degradations in the field.

Benjamin May received his MS in physics from the University of Greifswald. He served in several roles in 15+ years to implement and develop ADAS and AD systems for the mass market for different OEM customers worldwide. This includes especially vision systems. He is a co-founder of IEEE P2020 Automotive Image Quality Standardization working group to address the IQ KPI gaps. He serves as a strategic and technical advisor to several companies in the automotive domain. Benjamin is co-founder and management partner of obsurver to address the gap of sensor degradations in the field.

Gwen Daniel spent the first six years of her career developing computer program to model the treatment of skin with lasers and was awarded a PhD for her work in 2000. Subsequently Dr Daniel worked in a number of roles including Swansea University where she was responsible for the Virtual Reality cave. She joined Belron® in 2008 as the Technical Research Manager and is responsible for recalibration research and coverage in order to grow Belron expertise in the field and support the Belron businesses deliver world-class windshield camera calibration.

Chris Davies was awarded a PhD for his work on novel sensors utilizing optical and ultrasonic technology in 1994. Subsequently Dr. Davies worked at the University of Wales where he was responsible for delivering technology consultancy services. He joined Belron® in 2003 to head up the Research and Innovation team and is responsible for growing knowledge on causes of glass damage, future automotive trends and technologies. Chris has developed a deep knowledge of the complexities of automotive technology in particular, ADAS and their impact on the safety of Belron customers. In 2017, Chris was awarded the honorary title of Professor of Practice by the University of Wales, Trinity St David, 'in recognition of outstanding achievements in the subject areas which relate to the core mission of the University'.