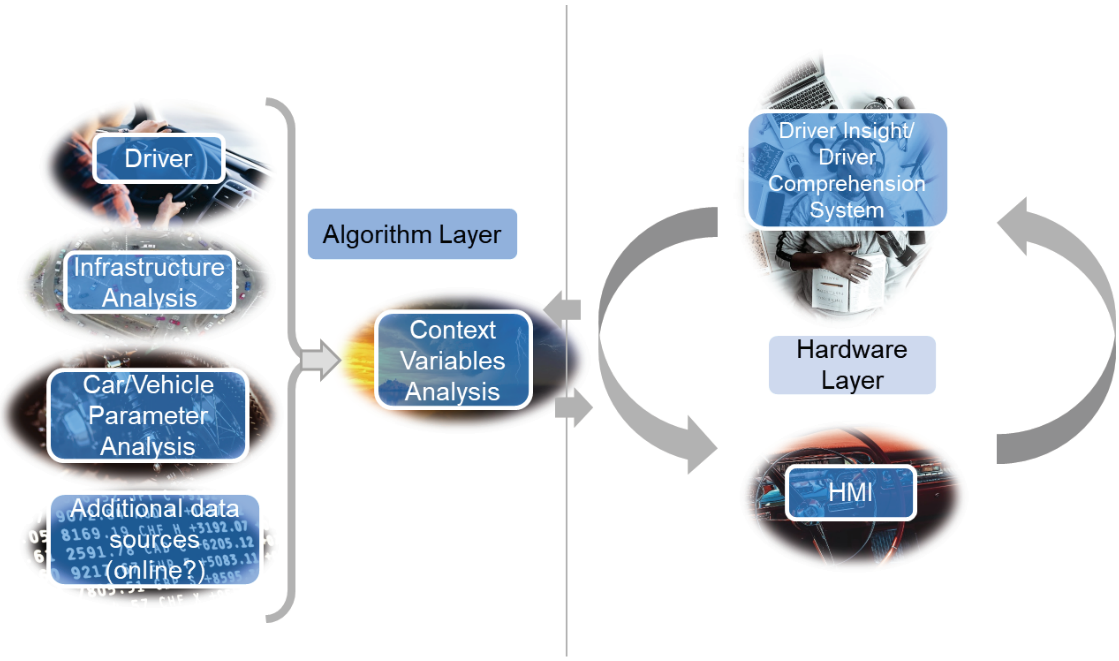
Driving Safety Scale and Scoring System: Turning Weak Evidence into Strong Safety Performance Scores (Tweaks)

Public report



Project within Trafiksäker automatisering - FFI - våren 2023
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Content

1. Summary

Detecting and understanding driver behaviors in real-time for safety modeling develop complex tasks due to the multitude of feature parameters associated with the driver, the vehicle, and the surrounding traffic. The objective of this pre-study is to classify driver behaviors according to a standardized metric that can be utilized for assessing safety contexts, which are then used to dictate adaptive HMI functions. Within this project, we employ a comprehensive definition of context, which encompasses diverse data modalities and then consolidates them into aggregated driving behaviors (Biondi, Strayer, Rossi, Gastaldi, & Mulatti, 2017). The raw data encompasses various aspects related to the driver, the vehicle, and the ambient traffic, enabling the formulation of multiple levels of context abstraction that unveil higher-level characteristics and decision-influencing features.

The detection of driver distraction relies on raw data obtained from onboard cameras and physiological sensors (Nees, 2021). Our Smart Eye project collaborator possesses certain levels of these solutions, which we proposed to further optimize in this pre-study, in view of other data sources. Along the vehicle and ambient traffic dimensions, the raw data sources are supplemented with CAN bus data, while ambient traffic use devices such as Lidar and GPS data. Both data sources are instrumented respectively by Autoliv and Viscando project partners, where Autoliv partners utilize the data fusion outcomes to infer driving HMI assistive functions such as speed, acceleration, and lane keeping as well as car-following gaps. The fusion process uses emerging Artificial Intelligence methodologies that are worked out by the University of Skövde project partner. This process consolidates driver and driving state features that are inherent to the physiological attributes of individual drivers and unique driving contexts that incorporate vehicle and traffic features. Vehicle dynamics information such as lane deviation and steering wheel motion contribute to the diagnosis of driving contexts, which can be utilized to estimate safety levels. Ambient traffic factors such as the volume and position of surrounding vehicles, can have a significant impact on driving safety, considering features such as congestion, traffic flow, following distance, intersection patterns, and speed differentials between lanes.

This pre-study presents the concept of driving analytics, which instruments AI-based data analysis methodologies to enhance the accuracy of context detection for assessing safety levels. On-board sensors, including eye-tracking cameras, are employed to analyze the driver's visual distractions by extracting features through image analysis techniques. Through the application of machine learning algorithms, future ADAS systems recognize various driving patterns, that were hidden from previous traffic safety solutions. This includes the combination of driver distraction levels, as well as vehicle dynamics and ambient traffic to enable the derivation of more precise safety indicators. These indicators are then utilized for HMI functions.

2. Sammanfattning på svenska

Det huvudsakliga bidraget från detta projekt är att ta fram utvecklingskriterier för ADAS utveckling i relation till olika trafikdatakällor för att producera och dela data om förarnas avsikter, beteende och trafikkontext, baserat på utveckling av metoder för informationsfusion för att skapa en medvetenhet om situationen, förutsäga dess utveckling inom en nära framtid och beräkna dess säkerhetsnivå. Data och resultat kommer att delas över ett molnanslutet fordon. Att kombinera information från olika datatyper och från flera fordon och infrastruktur gör det möjligt att få starkare bevis på den faktiska sanna situationen och dess utspel. Information om hur säker situationen är (kvantitativ säkerhetsnivå) och personliga körrekommendationer. denna säkerhets-information är endast användbar om den presenteras för föraren på ett tydligt, intuitivt och icke-distraherande sätt. HMI-koncept kommer att utvecklas med en hög nivå av anpassningsförmåga i relation till olika personer och trafiksituationer. Detta projekt skapar en mer intuitiv interaktion mellan föraren och fordonets körstödsystem.

Genom att använda sammansmälta data om andra trafikanters avsikter, den övergripande trafiksituationen och fordonsdynamik (för egna och andra fordon), kommer körstödssystem att skräddarsys till de specifika egenskaperna för att ge maximalt skydd. Förutom den kloka kombinationen av flera kontextuella data som ger nästa generations körstödsystem och de innovativa HMI-koncepten som förbättrar körupplevelsen i framtida fordon, automatiserar detta projekt också samspelet mellan dessa två komponenter. Körstödssystemet omvandlar data till evidensbaserade beslut medan HMI tillhandahåller gränssnittet genom vilket en förare förstår och agerar på dessa beslut. Nivån på HMI-interaktion anpassas således till de härledda sammanhangen som ligger till grund för besluten i körstödsystemet och anpassas ytterligare för att möta individuella förarprofiler.

Detta projekt utvecklar nödvändiga förutsättningar för en processmodell som gör det möjligt för drivande stödsystem att vidta lämpliga åtgärder som svar på förändrade förhållanden. Användarbehov och preferenser ingår i denna process, som påverkar till exempel överlämningsaktiviteter till eller från körstödssystemet. Denna aktivitet kan ses som en utarbetad modell av befintliga operatörshändelsesekvensdiagram (OESD) som användes för att öka situationsmedvetenheten och säkerheten för körstödssystem. Förutom att ge situationsmedvetenhet kan OESD-data skapa en virtuell representation av miljön, vilket gör att HMI-designers kan skapa uppslukande skärmar för att utforska och interagera med miljön i realtid. Till exempel prediktiva displayer som kan förutse användarens behov vad gäller navigationshjälp när fordonet närmar sig en korsning. HMI kommer att varna föraren om den potentiella risken, med tanke på användarens avsedda väg genom korsningen, genom att uppmana föraren att se efter cyklister innan svängning. Den interaktiva displayen ger ytterligare säkerhetsinformation om avsikterna hos fotgängare, cyklister eller andra fordon i närheten, såväl som varuinformation som tillgängliga parkeringsalternativ, POI-information (intressanta platser) eller omvägsalternativ (som svar på trafikstockningar eller vägar).

Det kontextmedvetna körstödsystemet övervakar föraren, fordonet och den omgivande trafikinfrastrukturen för att reglera HMI-kontroller och justera informations-presentationen. Till exempel kan mängden presenterad information skilja sig åt om fordonet är i autonomt läge eller körs i ett överbelastat område. Projektet använder nya datakällor från inbyggda kameror och fysiologiska sensorer för att sluta sig till förartillståndet (Engström et al., 2018; Galarza & Paradells, 2019; Nidamanuri et al., 2021). Förartillståndsdata bekräftas med fordonsdynamik och omgivande trafikdata för att profilera beteendet hos egofordonet, såväl som andra fordon och fotgängare i närheten. Kombinationen av dessa datakällor är ett annat centralt fokus i detta projekt, som gör det möjligt för nästa generations förarstödssystem att förstå körmiljön för att på bästa sätt hjälpa föraren med informerat beslutsfattande och förbättrad körupplevelse. Även om vissa av dessa datakällor har betraktats som i silos, främjar detta projekt deras sammanslagning för att kvantifiera säkerhetsnivåer. Nedan finns möjliga användningsfall för sådan datafusion:

- Förarstatus kan indikera distraktion, ouppmärksamhet eller trötthet. Dessutom kan fordonsdynamikdata stärka eller förfina dessa bevis med tanke på körfältshållning eller accelerationsmönster, särskilt om trafiken är lätt och inga faror finns i närheten.
- Fordonsdynamikdata kan visa oregelbunden körning. Men förarens tillstånd indikerar tillräcklig uppmärksamhet på vägen, men väderförhållandena är dåliga. Körstödssystemet kan då aktivera HMI för alternativa rutter med mindre isiga fläckar, snödrivor eller översvämmade områden eller med bättre sikt.
- Omgivningstrafikdata från infrastrukturbaserad mätning och realtidsrapportering från bilar kan härleda trafiktätheten och förstärka denna säkerhetskontext genom att överväga förarens tillstånd för att bestämma om man ska signalera försiktig körning eller om man ska föreslå bilföljande mönster efter en analys av pågående fordon dynamikdata.

Partners utvecklar en specifikation av nya HMI-koncept och processen för att fånga användarnas behov i ytterligare HMI-anpassning och personalisering. Det handlar om att förstå de olika typerna av förare, deras körbeteenden och deras specifika behov och preferenser (Rydström et al., 2022). Denna information kommer att erhållas genom förarövervakningsexperiment, undersökningar, intervjuer, fokusgrupper och etnografisk forskning. När användarsegment har identifierats används detta sedan för att definierar användarscenarier som beskriver hur det nya HMI-konceptet kommer att användas i olika körsituationer. Dessa scenarier är baserade på målanvändarnas behov och preferenser, såväl som kapaciteten hos körstödsystemet, som i sin tur behöver specifika relevanta data. Enligt första sidans figur är det en nödvändig utveckling inom trafiksäkerhet att skapa system som är mer flexibla för att interagera med bilförarna och hantera olika trafiksituationer där information om trafiksäkerhet också kan användas av olika fordon.

3. Background

The background is based on current research results within the general area of the levels of traffic safety. The project background areas are the use of traffic data, computational models, driver monitoring development, and driver interaction with driver support systems that improve traffic safety situations. According to FFI:s roadmap, this pre-study is directed towards the development of implemented sustainable solutions that are also accepted by users and society. This pre-study is supported by Autoliv, Smart Eye AB, and Viscando AB. These three companies are supporting a longer-term larger project that will be connected to this pre-study. The scientific basis of the project combines research from the areas of artificial intelligence (AI) and information fusion (IF) for the purpose of aggregating knowledge and fusing information to characterize contexts from a multitude of heterogeneous data sources. Driving contexts categorize multimodal data into aggregated driving behavior patterns.

The safety concept has been previously developed and evaluated according to different traffic situations and how safety information can reliably inform drivers about different critical factors and risks in traffic. Our pre-study has used Hollnagel et al. (2015), Aven (2022), and Schöner et al. (2021) as important references for the concept and computation of safety scores. The different kinds of safety according to these authors provide a basis for constructing more flexible safety scores. A recent article in The Guardian (Clarke, L. (March 27, 2022)) addressed the issue of how self-driving cars got stuck in the slow lane. One critical issue is the lack of AI systems to do what humans do, namely, to generalize from one scenario to the next. This is also stated as a problem with no solution for AI systems. The other major issue is the ability to handle rare traffic cases. Philip Koopman was one of the experts in the article, and he also has a recent publication, A Safety Standard Approach for Fully Autonomous Vehicles, (Koopman et al., 2019). One of the key topics that must be addressed is system-level safety metrics, which is what this pre-study project will work on to create a specific and larger innovation FFI-project.

4. Purpose, research questions and method

For ADAS development, the interaction between the calculation of safety in traffic situations and drivers is necessary. The calculation of traffic safety needs to be communicated to drivers at a level of trust. A major question has to do with the key factors that contribute to high levels of trust. The interaction between the two work packages is therefore a major factor for ADAS.

This pre-study project aims to create a basis for a traffic safety score that can be applied to different levels of autonomous vehicles AND be used in interaction with drivers of different ages, gender, and experience. The central question is the extent to which a safety score can be trustfully relevant for human drivers and autonomous vehicles. There are work packages to this central question: 1) to determine the relevant data sources and methods to create dynamic safety scores according to different traffic situations, and 2) create relevant contexts to test driver interaction with the safety scores. An important method is to calculate a safety score for driving with ADAS and AVs, for its feasibility. The purpose is to use the results of this pre-study to prepare a larger project where we can create and test the dynamic safety scores that provide drivers and levels of autonomy with critical traffic behavior information. The work packages are presented further below.

More specific aims related to the two work packages:
WP1
- What is a Safety Score?
- How to leverage methods for evidence combination to infer a concise and meaningful driving context as a condensate of the heterogeneous weak evidence stemming from raw data?
- What is an acceptable level of safety score confidence within ODD?

WP2
- Which HMI recommendations can create a sufficient level of trust for a safety score driving support system and infrastructure interactions?
- How can trust be measured according to the behavior and comments of the drivers?

All four partners collaborate in both WPs but there are different levels of collaboration among the WPs. The University of Skövde is the leader of both WPs, and Smart Eye is equally engaged in both as well. Autoliv is more highly engaged in WP2 whereas Viscando's emphasis is in WP1.

Safety Score WP1	What is the safety score?
Role: to contribute to the need for relevant data and safety indicators. University of Skövde	- Literature review - determine the relevant traffic contexts. - Methods for appropriate data analysis. - Identify key safety performance indicators.
Smart Eye Viscando Autoliv	- Identify current needs and potential contributions to the safety performance indicators. - Provide necessary data and current solutions for different Operational Design Domains.
Content: Safety score	- Determine the quantitative risk analysis and its role in determining the safety score.
Method: Information Fusion	- Determine the potential influence of relevant weak evidence that can be combined into actionable strong evidence for a specific driving context that allows for the calculation

	of the safety score
Delivery and evaluation	- Suggest a method and process for creating a reliable safety score according to scientific national and international criteria.
Trust and Interaction WP2	**The relation between safety score and trust?**
Role: to contribute to the need for relevant data, safety and trust indicators University of Skövde	- Determine the relevant traffic contexts. - Methods for appropriate data analysis. - Identify key trust interactive indicators.
Smart Eye Autoliv Major	- Identify current needs and potential contributions to the HMI factors in different traffic contexts. - The role of human cognition in understanding different traffic contexts in relation to safety.
Content: Safety score	- How can trust be manipulated by different safety scores according to genders?
Method: HMI	- How can trust be measured consistently and in relation to different traffic contexts?
Delivery and evaluation	- Suggest a method and process for creating a trustful safety score according to scientific national and international criteria.

5. Objective

The goal and potential of this pre-study project are empowering innovation for road transportation that is directed toward a sustainable society. The evidence framework to use is highly dependent on the task at hand, and how evidence should be combined might even be strongly dependent on the particular situation. This pre-study further investigated how the difference in existing variations of evidence theory might impact the calculation and usability of the safety score. Typical evidence frameworks that are available to be evaluated for this purpose are for example Bayesian and credal combination (Arnborg, 2006; Karlsson et al., 2011), Dempster-Shafer theory (Shafer, 1976), Modified Dempster-Shafer theory (Fixsen & Mahler, 1997), or the Transferable belief model (Smets & Kennes, 1994).

Karlsson and Steinhauer (2013) have evaluated what is known as precise and imprecise high-level information fusion (HLIF) methods with respect to a simulated scenario. This methodology will be a key computational tool for creating valid and useful safety scores. The interaction between computational methodology for safety scores and driver behavior is an area of important development for driver behavior in relation to different levels of autonomy. This is not just a computational issue but also an ethical and sustainability issue.

Figure 1 shows necessary data interactions (information fusion) between four main areas:

- traffic infrastructures
- external traffic interaction for vehicles and other road users
- internal vehicle behavior
- the development of driver monitoring for the driver understanding of the current and potential traffic situations.

A further area is the trust data results from driver support systems (ADAS). There is a current HMI study with Autoliv about the reaction time and trust comments. This study investigates the driver interaction with perceptual information about the traffic situation: Haptic, haptic + auditive, haptic + visual info, haptic + auditive + visual.

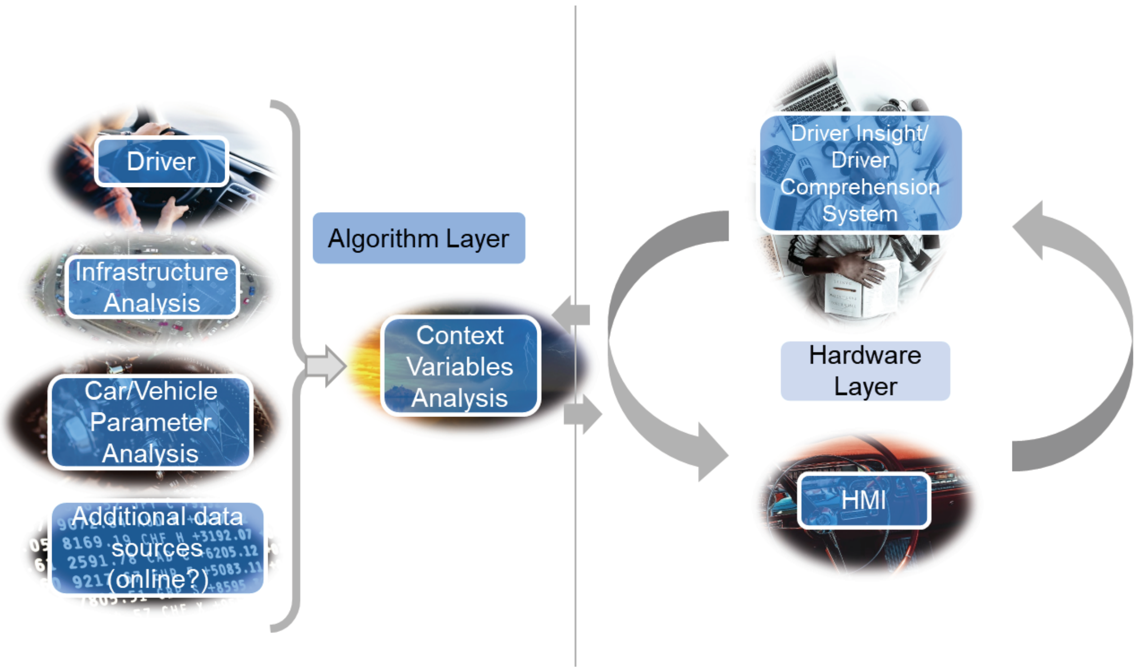


Figure 1. The interaction between different data sources and traffic situations that need to be used for ADAS-driver interaction.

The interaction between these main areas is necessary to develop the levels of safety and autonomy for driver support systems. Driver behavior and interaction with driver support systems depend on "early" collaboration between algorithm development and human understanding of the purpose of safety level information and potential behavior in intention prediction to create a much more adaptive interaction between driver support systems and driver decision behavior.

There is a need for data from connected vehicles (Ahmed et al., 2022) to increase the level of safety for driver support systems and interaction with drivers. Neural networks, deep reinforcement learning, and symbolic AI can provide low-level data implementations and high-level symbolic and rule-based implementations.

6. Results and deliverables

The results are presented from the two different WPs. The results from WP1 are computational methods as well as data sources and potential areas of connectivity between different traffic situations. The results from WP2 are within the context of the application of safey information/scores to HMI.

WP1

As described above, to calculate a safety score that quantifies the safeness (or safety level) of a situation, a multitude of aspects within the current traffic situation need to be considered. These are for example, the road conditions, the weather conditions, the driver's level of alertness, and the complexity of the traffic situation as a whole and with regard to each partaking vehicle, pedestrian, etc. specifically. While the road and weather conditions could be known by a system and the driver's level of alertness can be measured by a driver monitoring system, the complexity of the traffic situation is difficult to assess. It includes the identification of all traffic participants at the scene and understanding their intentions and their interactions.

We regard the task to establish a safety score of the situation to be an information fusion task. Where we describe information fusion as a research field that develops, deploys, and tests methods and techniques usable for the automatic or semi-automatic combination of data and information provided by different sources (see for example Steinhauer & Karlsson (2018)). The purpose of information fusion is to fuse the data and information into a coherent representation of the information. This is based on the idea that we usually can make better decisions given more information. While this is not necessarily always true, e.g., when information is conflicting, contradictory, deceiving, or very uncertain, it is generally a reasonable approach to consider all available information before concluding. Information fusion also allows us to infer (make explicit) new information from data that we did not know beforehand. Furthermore, the study of information fusion teaches us about uncertainty management methods with that the uncertainty within information can be handled appropriately when the information is fused. The methods studied within information fusion can stem from any other research area, such as mathematics, statistics, artificial intelligence, machine learning, optimization theory, etc. For any specific information fusion tasks, the best methods are chosen, adapted, and combined.

Analyzing the safety of a traffic situation is not an easy task. Humans are capable of doing it, and as an example, we can consider driving instructors that are required to have good situational awareness that allows them to judge if the driving student, in the given context of the traffic situation, will be able to handle the situation. The driving instructor knows what needs to be done, what can be missed by the student, what the possible consequences of all actions and inactions might be, also regarding the numerous different ways the other traffic participants might act or react. The instructor will evaluate their observations so that they can let the student drive on their own as much as possible, supporting them with information only when this is needed, but intervene just in time to avoid accidents or near misses when this becomes necessary.

Ideally, a safety score would not only provide us with information on how safe the situation is but also with information on what should be done to improve the safety, e.g., slow down to avoid hitting a pedestrian or speed up in order to avoid getting hit by a truck. It could potentially, based on observed driver alertness level and driver gaze tracking, identify that elements in the traffic scene have not been taken into consideration and hence could entail potential danger. A system that checks if the driver is about to do the “right thing”, can be used to support the driver better. A collision avoidance system could at the last instance prevent an accident but can also be used to find out when to support the driver and when to intervene. It would be if the interactive ADAS could identify what the driver is missing and make them aware of that by prompting the driver’s attention accordingly. This could be further coupled with intention recognition systems that are capable of inferring the intentions of other traffic participants (for an overview see for example Vellenga et al., 2022), e.g., a pedestrian might be about to cross the street. Here the ADAS could inform the non-alert driver and ask them to watch the pedestrian who might want to cross. Once the driver adhered to that suggestion, the safety score of the situation is slightly increased. In the contrary case, where the driver is alert and capable of driving through a complex traffic situation, the ADAS system should still be aware of all the potential dangers but there is no need to inform the driver about them when they already pay attention to them (which could for example be monitored by an eye tracking device). In this case, driver monitoring and traffic scene monitoring together would lead to a high safety score for the situation.

The trend within many application areas today is to use Deep Learning (DL) only; and, based on raw data from different and heterogeneous sources, develop a machine learning model, that provides a result, which in this case would be a safety score of the situation. However, using DL only bears a number of challenges. Firstly, there are many different choices that need to be made about the architecture of the Deep Neural Network (DNN) and several different DNN architectures might provide equal performance but are of different complexity. This is important because even if the computational power for onboard equipment in road vehicles has increased drastically in recent years, a DNN still needs considerable resources and might not be feasible and fast enough to provide in-time information (Semenova, Rudin, & Parr, 2022).

The second issue is the ability to explain the result. Not only do EU regulations require transparency (E Commission et al. 2021) but we also do not only want to calculate the safety score but also establish what needs to be improved in order to increase the safety score and to be able to prompt the driver accordingly. In the example above, it was the combination of the driver not being attentive enough in general and therefore missing the pedestrian who posed an immediate danger. The driver's attention now needs to be directed toward the pedestrian; hence the system needs to be able to identify the lack of attention and the danger through the pedestrian. Reasoning like this can more easily be done on a higher level of abstraction, where objects and the relationships between them can be identified as well as what-if scenarios of the future development can be played out.

A third and related issue is, of course, that neural networks need to be trained with loads of data, which is hard to obtain especially for the cases where the driving is of very low safety score and leads to accidents. Furthermore, even with a considerable amount of real data, machine-learning models lack robustness when it comes to rare or completely unseen situations (Hendrycks et al 2021). This leads to a next concern; the need for information about how certain or uncertain the system itself is about its prediction. Standard DL models cannot do that, but probabilistic DL approaches produce a probability distribution about the possible outcomes instead. And current research investigates if a so-called surrogate model can be used to estimate the uncertainty of a DL model (Vellenga et al, 2023) and might become useful in the future.

Taken together, the power of DL is an important resource for many parts of the problem but is not perfect for all of them. Hence, we suggest an approach where we use an information fusion method known as evidence theory, to combine and analyze information that is provided by multiple other methods, each being the best possible method for the respective task. For example, a driver monitoring system establishes the driver alertness level using a DL approach, the objects in the traffic scene are identified by their respective object identification and object tracking methods, e.g. using convolutional neural networks (CNN) for image classification, the possible intention of these objects are inferred using the respective intention recognition methods (for an overview of those see for example Vellenga et al, 2022), etc. The results of these separate methods are then translated into pieces of evidence, e.g., driver alertness, pedestrian intention, etc. and these are then combined with an appropriate evidence combination rule. Two important features of this are: that evidence will be provided as a distribution over all subsets of possible states and that the uncertainty within the evidence distributions can be measured and traced and it hence can be identified where the uncertainty arose from (e.g., Steinhauer & Karlsson, 2013). This will provide the basis for the ADAS system to know what help needs to be provided to the driver in the specific situation. Note that in evidence theory, the case of not knowing can be expressed, which is not possible in for example Bayesian approaches. To be able to say "I don't know" will

be important in order to cover situations where the system is not trained, e.g., rare cases or edge cases.
Here are a couple of key questions and suggested answers that will be used to further develop the safety information and the interaction with drivers.

What is a Safety Score?
A measure of a driver's safety behavior and performance
Calculated using telematics data:
Speed, acceleration, braking
Adherence to road safety guidelines
Our proposal: factor-in driver state and infrastructure data

Why do we need it?
Tesla uses it for driver coaching through its Tesla Mobile App:
Drivers see real-time scores
Specific events: e.g., hard braking or abrupt acceleration
Personalized feedback and recommendations to improve a safety score
Drivers become more aware of their driving habits.

ADAS "understands" a driver's behavior and adjusts interventions accordingly, e.g., to:
Determine when to intervene with lane keeping
Adjust car following distance or ACC speed
Emergency brake
Blind spot monitoring
Trigger HMI

Safety Score for Lane Keeping:
Safety score as a reference to intervene with lane keeping:
Vehicle data: steering angle, acceleration
Driver state: fatigue, drowsiness or distraction levels
Infrastructure: Vehicles in adjacent lanes

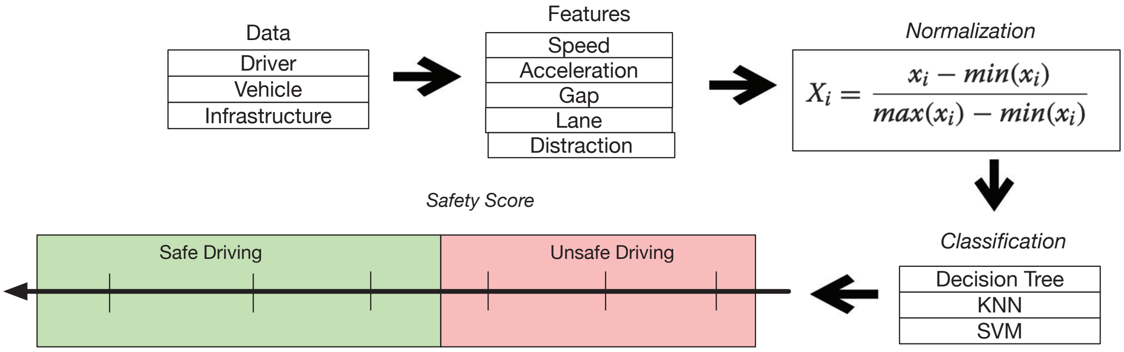
Rules of Engagement:
If safety score < threshold à Level 1 Warning
If safety score continues to drop à Level 2 Warning (HMI)
If safety score continues to drop à ADAS corrects vehicle position

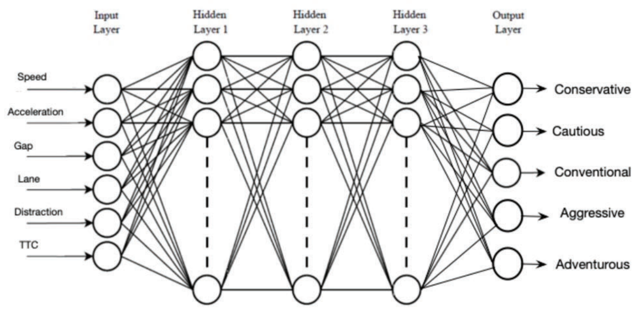
Safety Sore – Car Following & ACC
Safety score to avoid car-following collisions:
Infrastructure data: poor weather, reduced visibility, slippery road, changes in traffic flow, distance with lead vehicle, behavior of lead vehicle
Driver state: fatigue, drowsiness, distraction, substances, or anxiety levels
Vehicle data: acceleration and deceleration rates

Rules of Engagement:

If safety score < threshold à Level 1 Warning
If safety score continues to drop à Level 2 Warning (HMI)
If safety score continues to drop à ADAS increases the distance or adjusts speed

How to Compute Safety Score:





$$\begin{array}{cccc} & \text{Speed} & & \text{Distraction} \\ X_i = & \left[\begin{array}{c} x_1^{(1)} \\ \vdots \\ x_1^{(m)} \end{array}\right. & \begin{array}{c} \cdots \\ \ddots \\ \cdots \end{array} & \left.\begin{array}{c} x_n^{(1)} \\ \vdots \\ x_n^{(m)} \end{array}\right] \end{array}, \begin{array}{cc} & \text{Score} \\ Y_i = & \begin{bmatrix} y^{(1)} \\ \vdots \\ y^{(m)} \end{bmatrix} \end{array}$$

Manual driving (SAE L1)
If safety score < threshold -> Level 1 Information for corrective maneuver (HMI)
If safety score continues to drop or be below threshold -> Level 2 Warning (HMI)
If safety score continues to drop -> ADAS activates and corrects vehicle position

ADAS ACC active (SAE L2, L3?)
If safety score < threshold -> ADAS corrects headway

Description of safety score:
As a safety score can be applied in different ways like car sales the TWEAKS project has instead defined a real-time safety score that will benefit the driver or the automated vehicle in many driving scenarios.

A Real-Time Safety Score (RTSS) is a dynamic numerical or categorical representation of the safety status of a vehicle during operation. It provides instantaneous assessment and feedback based on a multitude of data inputs, including driver behaviour, vehicle condition, environmental conditions, and situational factors like traffic congestion and weather.

The score is generated by a complex algorithm that takes in raw data from various sources, processes and analyses the data, and then outputs a score that reflects the current level of safety. The exact calculation method can vary greatly depending on the specific design of the system, but the general principle is to assess risk and safety in real-time.

The Real-Time Safety Score can be used in several ways:
Driver Feedback:
The most immediate use of the RTSS is to provide drivers with feedback on their behaviour and the safety of their current driving conditions. For example, if a driver is following too closely to the vehicle in front, the RTSS could decrease, and the driver could receive a warning or suggestion to increase their following distance.

Safety Improvement:
Over time, drivers can use their RTSS to identify patterns in their driving that are unsafe and work to improve their habits. This could lead to safer driving overall and a reduction in accidents.

Insurance Pricing:
Insurance companies could use the RTSS as a factor in pricing their auto insurance policies. Safer drivers, as evidenced by a higher RTSS, could receive lower rates.

Fleet Management:
For companies that manage fleets of vehicles, the RTSS can provide a way to monitor the safety of their fleet in real-time. They could identify drivers or vehicles that are consistently unsafe and take corrective action.

Autonomous operation:
The RTSS could serve to evaluate the safety of their vehicles under different conditions, providing valuable data to guide the handling of the vehicle in real time.

The Real-Time Safety Score provides a quantitative measure of safety that promotes safer driving habits for both manual and autonomous driving, provides valuable feedback for drivers and fleet managers, and contributes to the development of safer vehicles and roadways.

Method:
Collect odds ratio
The method on how to transition from sensor data to odds ratios is a complex task requiring knowledge in data science, statistics, and a thorough understanding of the underlying physical phenomena the sensors are measuring. Follows an example of how this process could work:

Sensor Data Collection:

The first step is gathering sensor data from the vehicle. These can include data about speed, engine status, tire pressure, fuel level, and driver behaviour data collected from in-vehicle cameras, as well as external factors like weather and traffic conditions collected from external sensors and V2X communication.

Data Preprocessing:
Raw sensor data usually requires cleaning and preprocessing to ensure it's usable. This step might include dealing with missing data, handling outliers, normalizing data, etc. It's also essential to timestamp the data so that it ca§n later be correlated with specific events or conditions.

Feature Extraction:
Features are specific measurable variables that can be used in your analysis. For instance, if you have a camera aimed at the driver, you would need computer vision algorithms to extract features like "driver's eyes closed" or "driver not looking at the road."

Correlation with Events:
Now that you have your features, the next step is to associate these with certain outcomes or events. These events can be near-misses, hard braking events, actual crashes, etc. To do this, you'll need data about when these events occurred, which could be obtained from onboard vehicle systems, insurance reports, police reports, etc. Then, you can compare the features you've extracted with the occurrence of these events.

Statistical Analysis:
A statistical analysis is performed to establish the relationship between features and outcomes. This is where odds ratios come into play. An odds ratio is a measure of association between an exposure and an outcome. The OR represents the odds that an outcome will occur given a particular exposure, compared to the odds of the outcome occurring in the absence of that exposure.
For example, you might find that when the feature "driver's eyes closed" is present, hard braking events are twice as likely. This would give you an odds ratio of 2.0 for that feature.

Model Development:
Using these odds ratios, you can develop a predictive model that takes the current sensor readings, applies the odds ratios to the relevant features, and produces a real-time safety score. This model might be something simple like a weighted sum, or it could be a more complex machine learning model. The important thing is that the model incorporates the odds ratios you've calculated to weight the importance of different factors.

Validation & Calibration:
Lastly, the model should be validated with separate data to ensure its reliability and accuracy. Calibration might be necessary to align the model's outputs with real-world observations.

This is a simplified view of the process, and actual implementation can be much more complex. It requires skills in data science and software development, as well as a deep understanding of the vehicles, sensors, and conditions you're working with.

Evidence Theory:

Evidence theory, sometimes better known as Dempster-Shafer theory (Dempster 1969; Shafer 1976) is a framework that is able to deal with uncertainty in the form of non-specificity and discord. Within this theory it is possible to express uncertainty regarding an unknown random variable X for a given frame of discernment Ω. This random variable is defined by a mass function m:

$$m := 2^{\Omega} \rightarrow [0,1]$$

$$m(\emptyset) = 0$$

$$\sum_{A \in 2^{\Omega}} m(A) = 1$$

Any subset A of elements of Ω describes a focal element whenever its mass m(A) is non-zero. In addition to the mass function m, there are also the belief and the plausibility function, that are based on m defined as (Shafer 1976):

$$Bel(A) = \sum_{B \subseteq A} m(B)$$

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B)$$

The belief function Bel states to what extend A is supported by evidence whereas the plausibility function Pl states the degree to that A is not contradicted by evidence. Hence, belief and plausibility can also be described as the upper and lower bound for the probability of A, which means that the actual probability lies in between the belief of A and the plausibility of A i.e.:

$$Bel(A) \leq p(A) \leq Pl(A)$$

Through application of a pignistic transformation a single probability value for a focal element can be obtained (Smets and Kennes, 1994).

$$BetP(A) = \sum_{B \in 2^{\Omega}} \frac{|A \cap B|}{|B|} m(B)$$

We suggest that the results obtained from the different sub-systems (such as driver support, intention recognition for each object in the traffic scene, weather condition, etc.) will be obtained using the best possible method for them and will then be used to establish a mass distribution for possible safety score. For example: Let the frame of discernment be the safety score of the situation as Ω = {low, medium, high}. Then each information source will provide a mass distribution over Ω, which we would call weak evidence. These weak evidences can then be combined with an evidence combination rule into a combined evidence (strong evidence.). There are different ways of combining evidence and it is our statement, that depending on what information is combined at any step of the combination process, we need to choose the correct evidence combination method. The most well-known evidence combination operator is Dempster's rule of combination (Dempster, 1969) and will combine the evidences expressed by two mass functions m_1 and m_2 as:

$$m_{1,2}(A) = \frac{\sum_{A_i \cap B_j = A} m_1(A_i) m_2(B_j)}{1 - \sum_{A_i \cap B_j = \emptyset} m_1(A_i) m_2(B_j)}$$

This combination operator is commutative and associative (Dempster, 1969). However, it has the problem that it is undefined for the case where the conflict between the two mass functions is is zero. The literature, e.g. (Zadeh, 1984) provides examples where this operator hence yields counter intuitive results but Haenni (2005), has shown that there are ways to handle this problem. Furthermore, there are many alternative combination rules (e.g. Sentz and Ferson, 2002). What combination rule to choose will depend on the specific task.

The uncertainty that is implicit within a mass function can be measured (Klir and Smith, 2001). One example is the aggregated uncertainty, AU, defined by (Harmanec and Klir, 1994), which also fulfills all the requirements for such a function that have been established by Harmanec and Klir (1994).

$$AU(m) = max_{p(x) \in P(X)} \left[- \sum_{x \in \Omega_x} p(x) log_2(p(x)) \right]$$

where

$$P(X) = \left\{ p(X): Bel(A) \leq p(A) \leq Pl(A), \sum_{x \in \Omega_X} p(x) = 1, \; A \subseteq \Omega_X \right\}$$

As the name suggests, the aggregated uncertainty can be divided into measures for non-specificity and discord as described by Klir (2003).

How the mass functions are to be established for each information source needs to be established for every information source separately. It might be the judgement of a human expert that can be coded into an algorithm or it might be a machine-learning model that is trained by a multitude of examples. It is also possible to use an algorithm based on human expertise as a starting point and baseline model and then develop machine-learning models that will achieve better accuracy.

WP 2

Safety Score Based HMI Personalization
Deliver custom tailored interaction based on each specific driver score
Reflect driver needs in personalization decisions using scoring interface

Adapt the vehicle’s HMI elements and interaction paradigms to best fit a particular driver, given the context driven by the score

Use score to accommodate passengers by adapting HMI elements over all contexts

The use of safety score can be dependent on the autonomous level:

Manual driving (SAE L1)
If safety score < threshold -> Level 1 Information for corrective maneuver (HMI)
If safety score continues to drop or be below threshold -> Level 2 Warning (HMI)
If safety score continues to drop -> ADAS activates and corrects vehicle position

ADAS ACC active (SAE L2, L3?)
If safety score < threshold -> ADAS corrects headway

Trust and interaction
The Human-Machine Interface (HMI) plays a crucial role in facilitating effective driver interaction with driver support systems. Here are some of the most important HMI factors for ensuring successful interaction:

1. Clear and Intuitive Information Presentation: The HMI should present information in a clear, concise, and easily understandable manner. Visual displays, auditory cues, and haptic feedback should be designed to convey relevant information about system status, warnings, and interventions without causing distraction or confusion.
2. Contextual Awareness: The HMI should provide contextual information to help drivers understand the system's current mode of operation, its limitations, and its intended actions. This could include displaying the system's status, indicating the availability of support functions, and clearly communicating when the driver needs to assume control.
3. Consistency and Standardization: Consistency in HMI design across different driver support systems and vehicles promotes familiarity and ease of use. Standardized symbols, colors, and terminology help drivers quickly grasp the meaning of information presented, reducing cognitive load and potential confusion.
4. Timely and Relevant Alerts: Alerts and warnings should be timely, well-timed, and directly related to the driving situation. They should be designed to capture the driver's attention without causing undue stress or distraction. The HMI should prioritize and communicate critical information effectively, helping drivers make appropriate decisions and take necessary actions.

5. Customization and Adaptability: Allowing drivers to customize certain aspects of the HMI can enhance usability and driver satisfaction. This may include adjustable display settings, volume controls for auditory feedback, or personalization options based on individual preferences or needs. The HMI should also adapt to different driving situations, dynamically adjusting the information presented based on the current context.
6. Training and Familiarization: Providing adequate training and guidance to drivers on how to effectively interact with driver support systems is crucial. Drivers should be educated on the system's functionalities, limitations, and proper usage. This training should emphasize the HMI features and how to interpret the information presented, ensuring drivers are confident and capable of utilizing the system correctly.
7. Reducing Distractions: The HMI should minimize distractions and maintain driver focus on the driving task. This includes designing the HMI to avoid excessive information overload, intrusive alerts, or unnecessary visual clutter. Clear prioritization of information and minimizing unnecessary interactions can help reduce cognitive demand and support safer driving.
8. User Feedback and Evaluation: Collecting user feedback and conducting usability evaluations can help identify areas for improvement in the HMI design. User-centered design principles should be employed to iteratively refine the HMI based on driver input and real-world usage data.

By considering these important HMI factors, driver interaction with driver support systems can be optimized, leading to better understanding, effective utilization, and improved overall safety on the road.

Experiment testing the possible differences between the use of haptic information to drivers.

This experiment was done by two final year students within the User Experience Education Program. Paul Hemeren was their supervisor. They collaborated with Autoliv to experimentally test different combinations of haptic information as an interaction with drivers. Here is the abstract of the article and the link to the complete article. It is important to emphasize that even though the results were not significant, there was a clear pattern that suggests an effect of haptic information. There were only 10 participants in each of the four conditions, which was the most that could be used given the time frame for the project.

Abstract:

As vehicles become increasingly automated, it is important to have a functioning collaboration between the driver and the autonomous vehicle. In the case of semi-autonomous vehicles, the driver is not completely disengaged but still bears responsibility for driving. Since only certain functions are automated, the vehicle needs to be able to

give the driver clear feedback about the current driving situation and prompt the driver when he or she needs to resume control of the driving again.

One such type of feedback is anti-collision warning systems, where the vehicle emits warnings to prompt the driver to act and avoid an accident. Such type of warning can be of haptic, visual, or auditory modality. Previous studies show that there are several advantages to using haptic feedback. This study describes, based on retrieved literature and a participant survey in a driving simulator, the effect of haptic feedback on the driver's reaction time in frontal collision warnings. It is tested as its own modality as well as in combination with visual and auditory feedback.

The result shows that the driver's reaction time is shortest when warning with haptic feedback as its own modality. However, the results were not significant, as the difference in the mean values between the groups was not large enough to be generalizable. It is deemed important to further study in future investigations how haptic feedback affects the driver's reaction time, as a separate modality as well as in combination with visual and auditory feedback, in semi-autonomous vehicles.

Online link:
http://his.diva-portal.org/smash/record.jsf?pid=diva2%3A1773990&dswid=-4516

Use Cases

Use cases are critical contexts to test both WP1 and WP2. Driver state and driver monitoring are important traffic safety issues which are currently being addressed through regulatory requirements such as EU’s General Safety Regulations. While these systems and requirements are focused on the current state of the driver during the driving task, their activity history, sleep history etc. plays an important role in how these states would manifest. Research projects such as COPE and DrivER approach driver monitoring using consumer health tracking devices such as smartwatches and ECGs. These can also be important sources of data for the driver’s activity and rest history and can supplement the real-time driver state detection which happens during the drive. A safety score can be used as the basis for the driver monitoring, where the activity and rest history contributes to the score. This can also support with building and maintaining trust with the recommendations presented by the vehicle’s HMI.

This use case can be further investigated in monotonous, highway driving where there is an increased risk of boredom and sleepiness. A safety score built on evidence theory, in this case, which is connected to the driver’s activity and sleep history could present a more convincing recommendation to the driver to take a break. The recommendations can be made more interesting to the individual driver based on their preferences, for instance, a driver returning from a weekend of skiing is likely motivated to return home the same day to be able to go to work the next day. The algorithm and HMI can be present recommendations which the driver is most likely to comply. The actual perception of such recommendation needs to be evaluated in a study.

This approach can also be used to detect hands-on wheel and hand position in a more robust and fool-proof manner. Since the algorithms are taking into account what is happening inside and outside the vehicle, these hands-on detection systems can be designed to be context-dependent and demand drivers' to hold the steering wheel when it is most important.

The next use case for evidence theory-based safety scores are for the detection of sudden sickness (such as strokes or heart attacks while driving) and post-crash care. If evidence theory-based safety score can be standardized with medical triages, this can be used to inform emergency medical personnel and the nearest hospital of the state, criticality, vitality of the victims, etc. This could also be used to understand pre-crash factors such as driving under the influence of alcohol or drugs.

Safety Scores can be used to clarify the intention of the driver and vehicle when using ADAS such as lane-keep assist or automated driving functions such as traffic jam assist. Handover of the driving task from automated driving to an unwilling driver could be made safer through this, as this approach provides the driver with an assessment of the current safety level of the context and is based on the driver's current state and ability to respond to the request. If the driver is unable to respond in an appropriate manner, either an escalation strategy can be employed or a minimum risk strategy such as stopping can be executed. The evidence theory-based algorithm can also be used to complement the vehicle's ability to recognize that it is approaching its system limits, thus in an ideal world, reducing the risk of silent failures of driver support systems. Another aspect of this system is to tune the operating parameters based on the drivers' preferences, for example, a Lane Keep Assist can position the car either in the center of the lane or in a more defensive position towards the right edge. The system can also be designed to interpret the actions of other road users, such as an oncoming vehicle flashing lights at the vehicle. At an aggregated level, these systems can be designed to communicate with other vehicles (V2V) to forecast traffic flow patterns and offer drivers better route options.

7. Dissemination and publications

7.1 Dissemination

How are the project results planned to be used and disseminated?	Mark with X	Comment
Increase knowledge in the field	X	This increase in knowledge is the next phase of the interaction between drivers and driver support systems. This is the necessary next stage where computational modeling requires driver monitoring.
Be passed on to other advanced technological development projects	X	These results will be used to propose a larger project to work much longer to do experiemtal controls and applications.
Be passed on to product development projects	X	This is also a critical necessary factor given the necessary interaction between drivers and driver support systems.

Introduced on the market		
Used in investigations / regulatory / licensing / political decisions	X	This project builds on previous investigations and will also have as goal to contribute to further investigations within traffic safety.

7.2 Publications

This pre-study project did not have publication as a concrete goal since the purpose was to use previous research and interaction among different industries to create a suggestion for the next level of safety information development and interaction with drivers. Next step is to use the results of this pre-study to create more concrete experiments and applications together with industries and academic science projects. Despite the interesting results from the student project, there needs to be further testing to support the scientific suggestions in this project.

8. Conclusions and future research

Driver's role: Suggested areas of important driver tasks: maintaining control of the vehicle, obeying traffic laws, staying attentive, and making informed decisions based on the current driving conditions.

Clear basis for a system's role: The system's role refers to the functions and capabilities of the vehicle's onboard systems and technologies designed to support the driver and enhance safety. This includes advanced driver assistance systems (ADAS), autonomous driving features, and vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication systems. The clear basis for the system's role involves defining the system's functions, limitations, and how it interacts with the driver to ensure a safe and reliable driving experience.

Level of connection in the vehicle: The level of connection in the vehicle refers to the extent of connectivity and communication capabilities within the vehicle itself. This can range from basic connectivity for entertainment purposes to advanced connectivity enabling real-time data exchange with external sources, such as cloud-based services, navigation systems, or traffic management systems. The level of connection affects the availability of up-to-date information and the vehicle's ability to provide alerts, warnings, or assistive functions to the driver.

Operative Design Domain (ODD): The Operative Design Domain (ODD) defines the specific operating conditions, environments, and scenarios in which a particular vehicle or automated driving system is designed to function safely. The ODD encompasses factors such as road types, weather conditions, speed ranges, and geographic limitations. Describing the ODD involves specifying the boundary conditions and constraints within which the vehicle or system can operate safely and effectively.

Real-time method for detecting and judging a traffic situation: A real-time method for detecting and judging a traffic situation involves continuously monitoring the surrounding environment, collecting relevant data, and analyzing it to assess the current traffic conditions and potential hazards. Here's a description of such a method:

1. Sensor Data Acquisition: Utilize various sensors, such as cameras, radar, lidar, or vehicle-to-vehicle communication, to gather data about the surrounding traffic environment.
2. Data Fusion: Combine and process the data from multiple sensors to create a comprehensive and accurate representation of the traffic situation, including the positions, velocities, and intentions of other vehicles, pedestrians, and infrastructure.
3. Perception and Object Recognition: Apply algorithms and models to interpret the fused sensor data and identify relevant objects and their attributes, such as vehicles, pedestrians, traffic signs, and road boundaries.
4. Situation Assessment: Analyze the recognized objects, their dynamics, and the overall traffic conditions to assess the current situation, including the presence of potential hazards, traffic congestion, or critical events.
5. Decision-Making: Based on the assessed situation, make real-time decisions regarding appropriate actions or maneuvers to ensure safety and efficient traffic flow. This may involve adjusting speed, changing lanes, yielding, or taking evasive actions.
6. Execution: Implement the decisions by controlling the vehicle's acceleration, steering, and braking systems to carry out the planned actions and respond to the changing traffic situation.

A real-time method for detecting and judging a traffic situation should be dynamic, adaptable, and able to handle complex and rapidly changing scenarios. It relies on accurate and reliable sensor data, sophisticated perception algorithms, and robust decision-making processes to provide timely and appropriate responses to the traffic environment.

9. Participating parties and contact persons

UNIVERSITY OF SKÖVDE

The University of Skövde has led and managed this pre-study. Paul Hemeren (Associate Professor in informatics, male) has managed the project together with Yacine Atif (Professor in informatics, male), and Joe Steinhauer (Senior Lecturer and Researcher, female). All three actors are active traffic safety researchers from complementary areas such as computation, interaction and experimentation.

Autoliv Research (Johan Karlsson and Tejas Chandran) has focused on the development of the utility of a safety score and its relevance and trust for the drivers. This is in a sense related to a current EU-project (Mediator) which intelligently assesses the strengths and weaknesses of both the driver and the automation and mediates between them, while also taking into account the driving context (Ahlström et al., 2021). The trust of different levels of automation is related to driver behavior. Trustworthy safety scores can play a significant role for different levels of autonomy.

The focus for Smart Eye AB (Henrik Lind and Svitlana Finér) has been directed towards the collection of driver behavior factors that can contribute to and be influenced by safety scores. The collaboration between the companies in this pre-study project will provide the basis for the role that different data sources, computations and human-machine interaction have in increased traffic safety and trust for safety scores.

Viscando AB (Yury Tarakanov) contribute to the use of gathered naturalistic traffic data as well as the need to create new databases in order to create a basis for safety scores and an interaction with safety scores. Viscando contribution:

- objective, large-scale traffic movement and interaction data for situation understanding and traffic behavior prediction.
- Reference for expected/confusing, safe and unsafe behaviors in traffic – without driver bias
- Useful for both ADAS and AD

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