

A Safety Score for the Assessment of Driving Style

Hans-Peter Schöner ^a, Paolo Pretto ^{b*}, Jaka Sodnik ^c, Bostjan Kaluza ^c,
Mojca Komavec ^c, Damir Varesanovic ^c, Hanna Chouchane ^d, Jacobo
Antona-Makoshi ^d

*^aIFO-Consulting, Ammerbuch; ^bVirtual Vehicle, Graz; ^cNervtech, Ljubljana; ^dJapan
Automobile Research Institute JARI - SAKURA project, Tsukuba*

*corresponding author:

Dr. Paolo Pretto

Virtual Vehicle Research GmbH

Inffeldgasse 21/A, 8010 Graz, Austria

Tel: +43 316 873 -9720

paolo.pretto@v2c2.at

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Objective: Road traffic laws explicitly refer to a safe and cautious driving style as a means of ensuring safety. For automated vehicles to adhere to these laws, objective measurements of safe and cautious behavior in normal driving conditions are required. This paper describes the conception, implementation and initial testing of an objective scoring system that assigns safety indexes to observed driving style, and aggregates them to provide an overall safety score for a given driving session.

Methods: The safety score was developed by matching safety indexes with maneuver-based parameter ranges processed from an existing highway traffic data set with a newly developed algorithm. The concept stands on the idea that safety, rather than suddenly changing from a safe to an unsafe condition at a certain parameter value, can be better modelled as a continuum of values that consider the safety margins available for interactions among multiple vehicles and that depend on present traffic conditions. A sensitivity test of the developed safety score was conducted by comparing the results of applying the algorithm to two drivers in a simulator who were instructed to drive normally and risky, respectively.

Results: The evaluation of normal driving statistics provided suitable ranges for safety parameters like vehicle distances, time headways, and time to collision based on real traffic data. The sensitivity test provided preliminary evidence that the scoring method can discriminate between safe and risky drivers based on their driving style. In contrast to previous approaches, collision situations are not needed for this assessment.

Conclusions: The developed safety score shows potential for assessing the level of safety of automated vehicle (AV) behavior in traffic, including AV ability to avoid exposure to collision-prone situations. Occasional bad scores may occur even for good drivers or autonomously driving vehicles. However, if the safety index becomes low during a significant part of a driving session, due to frequent or harsh safety margin violations, the corresponding driving style should not be accepted for driving in real traffic.

Keywords: driving style score; safe driving index; safety index; cautious driving; preventive measures

Introduction

The German Traffic Code (STVO 2013) – similar to other traffic codes in the world (Highway code UK 2020; Japanese Road Rules 2020) – has a strong focus on the prevention not only of collisions, but also of dangerous situations as precursors of collisions and other accidents. The German traffic code specifically states:

- (1) Participation in road traffic requires constant caution and mutual consideration.
- (2) Any person who participates in the traffic must behave in such a way that no other person is harmed, endangered, or – at least not any more than is unavoidable under the circumstances – hindered or bothered.

The requirement of not harming anybody implies not causing a collision. The requirement of not endangering others implies reducing exposure to collision-prone situations, effectively acting as a safety margin for unexpected collision scenarios as well as for misjudgments or misbehaviors of others (König 2013; Schöner 2019). While both of these requirements have a clear priority over not hindering or bothering traffic flow, hindered or bothered traffic participants tend to take additional risks to circumvent obstacles, which also make them relevant for safety. This should be avoided whenever possible.

Granting permission for autonomous vehicles to be used on public roads may be akin to granting a license to a human driver. The latter requires the authority providing the license to have sufficient evidence that the driver possesses the requisite skills to safely drive in a complex traffic environment. Following this rationale, several programs around the world are developing test suites to assess the behavior of autonomous vehicles on proving grounds before releasing them onto public roads (Kitajima 2018, Ploeg 2018, Peng 2019). These programs, however, tend to focus on a limited number of pre-defined scenarios, which may be insufficient to ensure safe behavior in real traffic on public roads. Considering the requirements of the traffic code, it is important to not only measure the necessary skills to avoid collisions, but to also provide safety margins and take other safety-related behavior into account for an objective assessment of safe behavior in traffic.

The assessment of human ability to drive safely in real traffic when issuing a driver's license is primarily focused on the driver's ability to look ahead, to anticipate and avoid dangerous situations, to drive carefully and in a predictable way for others, and to judge and act according to both safety and traffic flow. While safe handling of crash-imminent situations is in fact one important feature of autonomous vehicles, anticipative strategies, including the use of adequate safety margins, must also be considered before releasing such vehicles into public roads traffic. This successful human strategy of accident prevention can be translated to assess the safety of autonomous vehicles. We must not wait for collisions to gain an impression of the safety of the driving style. For this purpose, adequate, objective and quantitative measures of the driving style, which addresses the complexity and criticality of traffic situations in a safe manner, need to be implemented. This measure of driving style should consider both crash-imminent situations (with the corresponding fast transient reactions close to safety margins) as well as anticipative strategies (considered as slower actions when still being well within safety margins).

A review on quantitative measures of safe driving is included in the appendix. It can be derived that a binary distinction between safe and unsafe driving seems inadequate to account for the broad variety of traffic behavior. Here, we propose an approach to overcome this limitation.

This paper describes the concept, development and verification of an objective scoring system that assigns safety indexes to observed driving style and aggregates them to provide an overall safety score for a given driving session. The safety indexes are inferred from a statistical analysis of human driving style (by adopting safety margins and behavioral patterns that are considered acceptable by humans) as well as from additional knowledge about dangerous behavior in traffic (by penalizing clearly unsafe actions and rewarding preventive and mitigating actions).

Methodology

The methodology of this research comprised three steps. *First*, a safety score concept was developed based on the hypothesis that (a) usual levels, dynamics and reaction times of driving parameters can be found by observing real traffic data, and (b)

that a quantitative safety assessment may be established by matching the parameter ranges with a continuous scale. *Second*, a large dataset of German highway traffic, created by Aachen University within the public German Research Project PEGASUS (Krajewski 2018), was used to extract acceptable parameter ranges of manual driving behavior. The data were analyzed with a newly developed algorithm that accounts for vehicle dynamics parameters and interactions among different vehicles. The extracted parameters were then matched to driving safety indexes. Those indexes were derived from statistical distributions of driving parameters within specific maneuvers. *Third*, the sensitivity of the score was verified by the ability of the algorithm to discriminate between normal and risky driving styles along 10 km of simulated driving.

Figure 1 shows an overview of the different steps for the parameter extraction on the basis of observed maneuvers in the data set, and the subsequent allocation of safety indexes to maneuvers of the driving session to be assessed by the safety score.

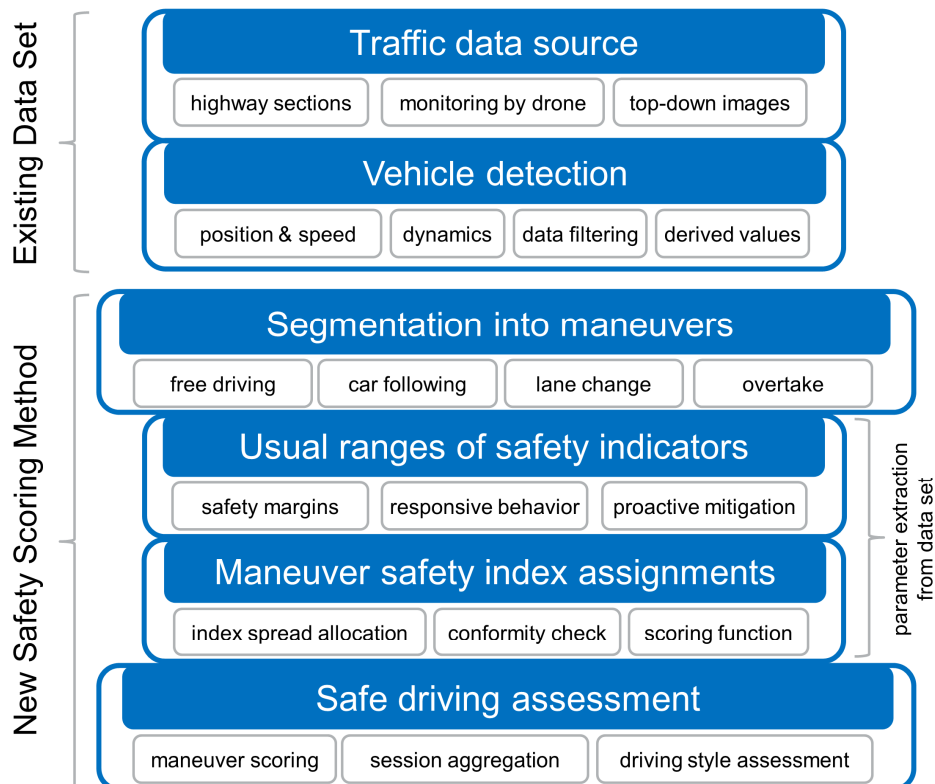


Figure 1. Processing steps of the safety score development: for each maneuver type safety indexes are assigned to safety relevant parameters from the data set and

combined into a maneuver scoring function; the driving style is assessed for each single maneuver and aggregated into a score for an entire driving session.

Safety score concept development

Understanding the usual level, dynamics, and reaction times of driving actions in a given environment is a prerequisite to developing a score of safe behavior for vehicles that are to be driven within that environment. Difficult, challenging or even dangerous traffic situations are characterized by the fact that staying on the road or away from other objects can only be achieved by *unusually* intense or fast actions compared to the usual level or dynamics of control actions (Schöner 2019). Danger is also perceived when temporal or spatial safety margins are reduced by neighbouring traffic participants such that there would be insufficient space or time to perform preventive actions if foreseeable situations with high risks of damage or injury should arise (Mobileye 2018).

The *usual* level, dynamics and reaction times of driving actions can be found by analyzing a sufficiently large and diverse set of driving data of the specific traffic environment. The data source should contain a wide range of normal and challenging maneuvers under different traffic and environmental conditions. Collisions as typical unusual events can be (but need not to be) part of the analysed data. The statistics of the physical motion of individual vehicles driven by human drivers in such a data set contain the parameter ranges of a “usual” and safe driving style. Such traffic data sets, preprocessed with respect to tracking of every single vehicle and evaluation of their physical motion parameters, are available by now (Krajewski 2018).

Every driving environment has characteristic maneuvers with different motion patterns, constraints, durations, and inherent risks; as such, safe behavior depends on different parameter sets in these categories. For this reason, the segmentation of driving into maneuvers is essential for a safety assessment and the first step of data analysis. For highway driving, the maneuver types *Free driving*, *Car following*, *Lane change*, and *Overtake* were identified and analyzed.

By looking at each maneuver in detail and extracting the usual parameter ranges that characterize them, individual parameters can be judged with respect to their relevance to safety. We looked for three different types of parameters which are relevant as safety indicators: first those related to *safety margins* (e.g. safety distances, following times, time to collision, speed limit), second those related to *responsive behavior* (e.g. reaction time, acceleration, relative distance change), and third *proactive mitigation* actions (e.g. early speed reduction, timing for opening a gap). These parameters can be observed in a given maneuver and the parameter values can be measured; their values show typical ranges.

This observed parameter distribution serves as a basis for assigning a safety index as a first quantitative safety assessment of the maneuver based on the individual parameter value, ranging between 0 (unacceptably unsafe) and 1 (reliably safe). At least at one end of the parameter distribution there is a clear impairment on safety when definitely exceeding safety margins, or when showing extreme (too low or too slow) responsive behavior. In this unsafe region a safety index of 0 is assigned. In the centre of the distribution there is a range with acceptable behavior with a safety index of 1. Since general behaviour does not switch from safe to unsafe instantaneously, we introduced an *index spread*, in which the safety index changes from 0 to 1 for respective parameter values. The shape of the parameter distribution may provide the acceptable (“proven by usage”) parameter ranges found in the human driver population. However, the process requires additional engineering expertise. Especially the tails of the distributions have to undergo a critical *conformity check*, whether the respective behavior is in line with objective safety requirements or whether it represents unacceptable behavior, like significant speeding or very low safety distances. Two examples are discussed in the results section of this paper. Since several parameters characterize one maneuver, their respective safety indexes have to be combined to form a final safety *score function* of all relevant parameters for the scoring of a complete maneuver.

The assessment of a complete drive in a summarizing score is based on a time dependent recording and weighted averaging of the scores of the single maneuvers – low maneuver ratings should be given specific attention. Single low values in the

driving style score might arise from endangering behavior of *other* traffic participants, but consistent low values are a strong indication of *own* deficiencies. If the score for safety often falls below a certain percentile threshold (e.g. 15th percentile would imply that 85% of the driving population perform better), then the driving style should be reviewed.

Real traffic data analysis

For identification of the normal parameter ranges the *HighD dataset* was adopted (Krajewski 2018). The dataset contains drone video recordings from six different highway locations around Cologne, Germany. The recordings took place between 8:00 and 19:00 in good weather conditions. In total 60 top-down recordings were captured in 4k (4096x2160) resolution at 25 frames per second. Road segments of approximately 420 meters of length were covered in each recording. Each recording had an average duration of 17 minutes, which amounts to a total recording time of 16.5 hours. In the post-processing stage, 110,000 vehicle (car and truck) trajectories visible for a median duration of 13.6 seconds were extracted to form the dataset. The videos captured a wide range of different traffic situations from fast free driving to slow stop and go. No collisions were recorded within the dataset.

In the current study, the post-processed trajectories were automatically segmented into the four essential highway driving maneuvers as mentioned above. Each of these maneuvers was assigned a different set of characteristic parameters (see appendix). For each maneuver type, the values for the characteristic parameters were sampled, and their statistics were analyzed. Parameter ranges were identified through statistical analysis; their allocation to the safety index spread was based on driving physics, on a review of prevailing traffic regulations, and on existing safety evidences from different sources in the literature (Kodaka 2003, Winner & Schopper 2016; Winner 2016). Two specific examples are discussed in the results section of this paper.

Safety score sensitivity test

The ability of the scoring algorithm to discriminate between a *normal* (safe) and an *risky* (less safe) driving style was verified by running a sensitivity test performed in a driving simulator (Komavec 2019) with two volunteer drivers. The simulator comprised

a static driver environment mock-up and three 49" screens providing 180° field of view, including rear view mirrors. The experiment was performed on a simulated straight three-lane highway 10 km sector with low traffic density. Each driver was asked to drive the same sector six times. Before the drives, each driver received different instructions to predispose them to either *normal* or *risky* driving. The *normal* driver was instructed to drive smoothly while remaining aware of his behavior and the safety of other traffic participants (i.e. to keep safe distances and constant speed/distance whenever possible). Additionally, the driver was instructed to drive as if he was not in a hurry and was driving with other people in the car. The *risky* driver was instructed to drive roughly with little safety awareness (low safety distance, fast approaching, or unstable distance/speed behavior) as if he was alone in the car, late, and still wanted to reach the destination on time.

Results

Safety index assignment based on real traffic data

Figure 2 and Figure 3 show two examples of the processed highway traffic data in terms of number of occurrences for temporal headway and time to collision (TTC) parameters, respectively. Each figure includes at the bottom a safety index allocated to corresponding parameter ranges. The blue bars show the absolute occurrence of the parameter and the orange dotted line shows the cumulative percentage of occurrences.

The distribution in Figure 2 shows that the temporal distance of car following has a usual range (20th to 80th percentile) between 1s and 3.5s. Very large parameter values might have no relevance for safety (but rather for traffic flow). As such, for parameters above a certain value (3s in this case) the maximum safety index of 1 is allocated. Values below one second down to 0.5s however are significant for safety performance and should lead to low safety indexes.

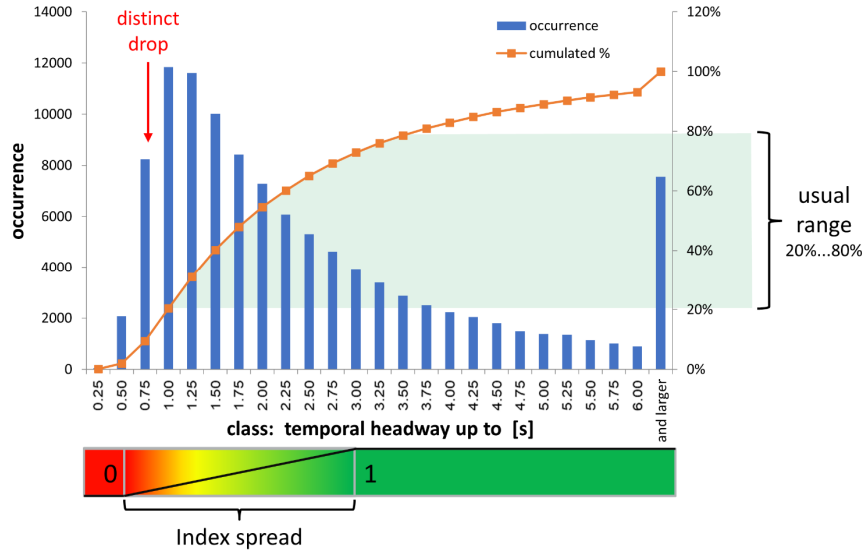


Figure 2. Assignment of a safety index for “temporal headway” parameter in “car following – steady state” maneuvers.

The distribution in Figure 3, showing the occurrence of time to collision (TTC) when approaching dynamically, suggests that human drivers no longer care about TTCs above 6s; allowing for the safety index to be set to 1 constantly in this region.

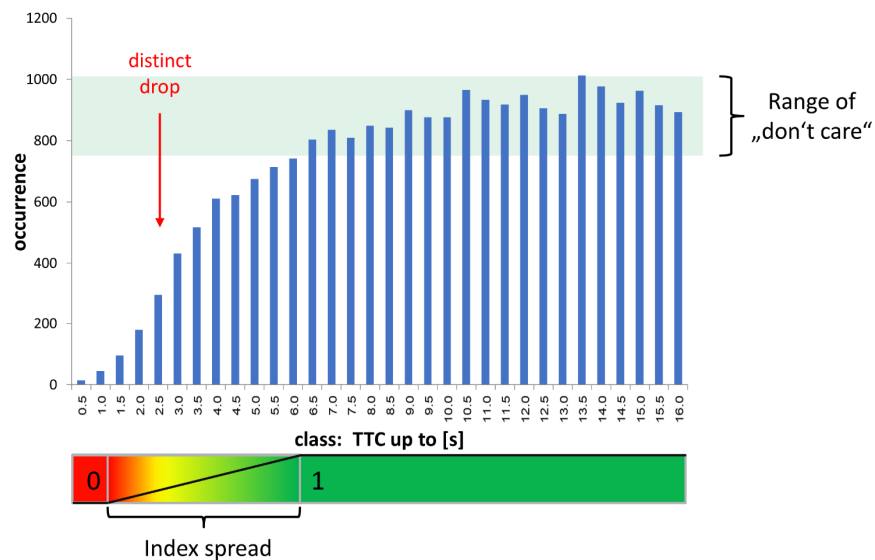


Figure 3. Assignment of a safety index for “TTC” in “car following – dynamic approach” maneuvers.

In both figures the distribution of human driver behavior in regular situations shows a ‘distinct drop’ (change of curvature) in the histogram close to the unsafe end of the distribution. The score spread for the safety index of the parameter is designed to reach quite low values close to this point in the histogram.

Safety score sensitivity

Figure 4 shows the development of the driving style score over time, comparing typical drives of the two differently instructed drivers: a *normal* driver (in blue), and a *risky* driver (in red). As horizontal axis the driven distance in km is used, while the vertical axis shows the aggregated safety score (ranging from 0 “unacceptably unsafe” to 1 “reliably safe”). The score was updated after completion of every new maneuver as a linear combination of the previous aggregated score and the safety score assigned to the new maneuver. This kind of score aggregation results in steps at the end of the maneuvers, as clearly visible in Figure 4.

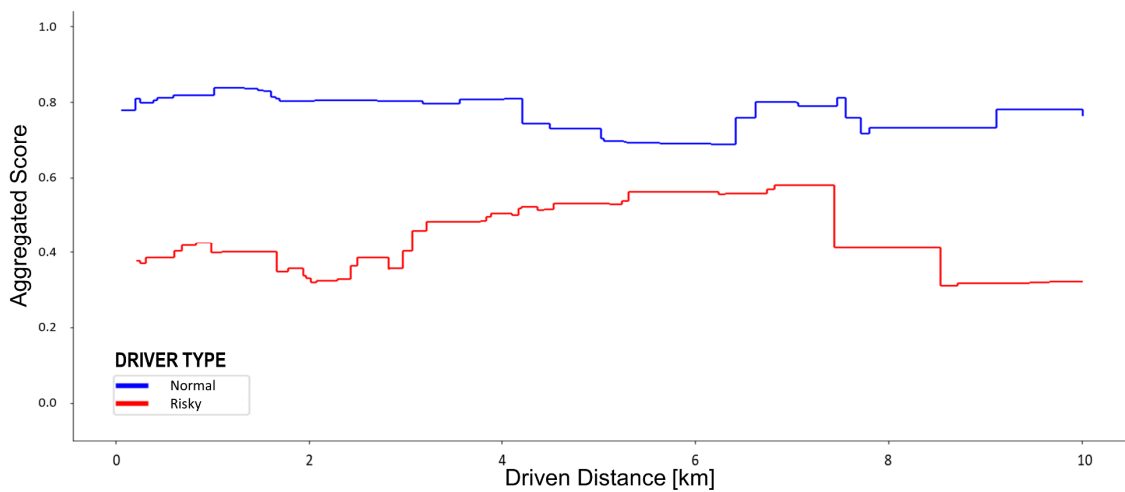


Figure 4. Comparison of the development of the driving style score for a *normal* and a *risky* driver

While the *normal* driver reaches an almost steady score around 0.8, the *risky* driver shows a significantly lower score between 0.3 and 0.6 with significantly larger fluctuations.

Discussion

Safety index assignment

The ‘distinct drop’ in the distribution observed for low values of temporal headway and time to collision parameters (Figure 2 and Figure 3) can be interpreted as a natural tendency of most human drivers to avoid this region, which constitutes a clear indication of perceived danger in these parameter ranges. A low value of the safety index at this point should clearly indicate this perception of danger. A few situations with lower indexes might occur anyway (without a collision), however a safety index of zero is assigned below certain parameter values when they clearly provide insufficient safety margins.

It may be argued that the linear relation applied to the parameter between index 0 and 1 may not be the most suitable to represent the histograms obtained from the traffic data. However, we believe that in this context, the exact shape and mathematics behind the index allocation function is less relevant, as discussed thoroughly with the concepts of fuzzy logic (see Application aspects); practicability and applicability are prioritized. Moreover, the identification of a ‘distinct drop’ is to be intended for demonstration purposes, as it is based on visual inspection of the plot and on rather qualitative criteria. However, regardless of the precise value and criteria, the goal is to produce a safety score that captures the transition from safe to unsafe driving style within a realistic range of behavioral differences.

Human drivers base their behavior and safety margins on situations that they expect to happen, mostly because they have already experienced them. For this reason, situations that can cause rare accidents but with a high injury impact may not be represented adequately in the behavior statistics. Safety index conformity checks and corrective techniques supported by additional knowledge based on, for example, experiments focused on rare situations (Kodaka 2003) and previous experience developing driver assistance systems (Winner & Schopper 2016; Winner 2016), may be considered for the assignment of safety indexes specifically at the tails of the parameter distributions. Such knowledge-based corrections were applied especially for excessive speeding and for extremely short safety distances (see discussion of figure 2).

Depending on ambient conditions that were not present during the collection of the statistical data (like bad weather causing impaired sensing conditions, or reduced road friction), the safety index spread might be shifted to higher temporal headways or TTC.

Application aspects

The concept proposed in this study has been shown to work in highway driving environments and we expect it to work for other traffic environments as well. However, the latter requires evaluation of acceptable parameter ranges in further relevant maneuvers. As more datasets become available, including urban environments, behavior in intersections and merging zones, extending the evaluation of the applicability of the proposed concept to different environments is a matter of time effort and diligence.

The driving style score which is established in the described way depends on the specific statistical data used. This way it is able to provide adapted scores for different local driving styles, indicating whether the vehicle's style is able to blend smoothly into local traffic. Further, the score has a "fuzzy" (Zadeh 2008) nature, because different developers might achieve slightly different quantitative results. Nevertheless, it is able to identify the critical situations with respect to safety while driving, indicating when it is time to increase safety distance, to reduce speed, or to improve cooperative behavior.

Although the data set we have used does not include collisions or situations with very harsh braking or steering, it is guaranteed that the applied algorithm does assess such situations with a very low safety score, either because the resulting safety margin parameters reach very low values, or the responsive parameters (like accelerations and TTC) show values distinctly out of the usual ranges. Due to the inclusion of parameters which measure the position in the lane (e.g. in *Free Driving* maneuvers), even driving mistakes like departing from the lane or road are covered.

Implementation aspects

The path planner in any autonomous vehicle controller is expected to have all the relevant parameters available, because the choice of the best trajectory and the

suitable speed need basically the same rating. However, such performance measures would normally not be available for vehicle validation. As a monitoring feature during development and testing and at least for certification purposes, it would make sense to have these measures available and documented. The path planner, however, would not normally look back to judge its own performance in the case of a surprise or other new information that is only available at the end of a driving maneuver. As such, we believe our work could be useful for future implementation as a consequent extension to the path planner in autonomous vehicles.

Further work and possible applications

We have shown so far that safety indicators can be extracted from objective driving data, evaluated on the basis of statistics of a large highway data set (at good weather conditions), and aggregated to provide a quantitative safety score for a complete drive. Preliminary comparisons of the resulting scores with driving instructor assessments came to good agreement. Further verification and validation work is needed, for example by comparing the results of our data-based approach to the recent physics-based approach of Mattas e.al. (2020) and by applying this method to different data sets, or in real world tests. This will result in fine tuning of the index spreads, the parameter weights and score aggregation functions, and it will help to give a more precise view on the role of risky driving for traffic safety.

Once established and validated, this objective measure can provide a repeatable quantitative a-posteriori judgment of how far the maneuvers in a complete driving session were on the safe side compared to existing and legally required behavior in traffic. Such a score can provide not only a measure for testing and certification, but also for a continuous improvement and even automatic learning of a good driving style.

We believe that this kind of safety score can be extended to other driving environments by including more driving maneuvers and weather conditions. Our approach can be extended to assess in a similar way the dimension of cooperative, hindering, or bothering behavior (resulting in a *traffic flow score*). A third dimension assessing driving comfort (*comfort index*) can also be established accordingly.

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Appendices

Glossary - The concept of Driving Style SCORES based on INDEXES

In our work we use and propose the following nomenclature concept:

Driving Style Score is the umbrella term that indicates and assesses how a vehicle is moving in general on the road with respect to the surrounding conditions for a certain driving period. The Driving Style Score may consist out of different components, each with specific focus; some of them have already been investigated (one of which is described in the current document), while others can be added later on. Those components are, so far, the *Safety Score* and the *Flow Score*. Another could be for example, a *Comfort Score*. The scores are calculated based on temporally changing indicators and quantitatively measured by indexes (*Safety Index*, *Flow Index*, *Comfort Index*) that are attributed to physical driving parameters on the maneuver level based on time/distance among vehicles and their dynamics.

A *maneuver* is defined in detail as a set of (relative) vehicle motions and can be described by characteristic parameters that are also dependent on the driving context (e.g. between highway and city driving). Examples of maneuvers are *vehicle following*, *lane change*, *overtake* or *parking*.

The *Safety Score*, therefore, represents the aggregated form of several *Safety Indexes*, which are extracted from statistical analyses of real manual driving behavior, complemented by practical considerations for implementation in real scenarios, and which are assigned to each maneuver upon completion.

A *Driving Style Score* for a complete driving session, compiled from its temporal, maneuver-oriented components *Safety Index*, *Flow Index* and *Comfort Index*, can provide a similar judgment of traffic scenarios as a human co-driver or driving instructor would perceive it: a fuzzy but repeatable a-posteriori judgment of whether a driving situation was safe, difficult, critical or even dangerous (*Safety Index*), whether it was cooperative, hindering or bothering (*Flow Index*), or whether it was smooth, sporty, or rough (*Comfort Index*).

Related work on quantitative safety measures

In the literature we find several approaches to quantitative measures for safe driving in

traffic. Especially in the context of driver assistance systems the limits of driver and vehicle performance with respect to collision avoidance have been analysed and studied, but quantitative values either apply only for very specific use cases or they are given in a certain range.

Breuer et.al. (2016) state the physical quantities which are relevant for safety assessment and which are analyzed in vehicle tests and in driving simulators. For highway speeds, driving safety depends predominantly on possible reaction times and reaction levels for sudden actions of a preceding car, or for unexpected objects on the road. Thus, important safety indicators are longitudinal safety distance and enough time margin for a suitable reaction.

MobilEye (2018) published a concept called RSS (Responsibility-Sensitive Safety) which focuses on longitudinal and lateral safety distances, precisely calculated by applying the well-known physics of vehicle dynamics, and it claims to leave out the behavior of a human driver. Some parameters in RSS are based on assumptions, they still need to be determined by regulations for application of the method. These model parameters could be defined based on *typical* reaction times, *normal* braking decelerations and *standard* weather conditions. But no matter which parameters are chosen, there are always additional (more or less rare) scenarios in which such parameters would not guarantee collision-free driving. No parameters could be defined yet for a clear cut between *safe* and *unsafe* driving according to the RSS model.

Including the human behavior makes the case even more difficult: according to Abendroth (2016), human reaction time ranges from 0.7s for expected situations, 1.25s for unexpected routine situations and up to 1.5s for emerging surprises. In normal car following situations a reaction model of Chandler (1958) assumes a delay time between perceiving speed differences and corrective accelerations. An evaluation of driving patterns in the HD data set (Krajewski 2018) based on such a model reveals average car following reaction times of 1.4s, but with a wide standard deviation of 0.7s. In view of these large variations, there is no precise method to decide which parameter value for human reaction time should be used as design parameter for a system with high safety standard and for traffic situations involving human drivers.

AAA Foundation for Traffic Safety (2009) reviewed the published scientific literature on aggressive driving, citing the definition of *US National Highway Traffic Safety Administration* (NHTSA) of aggressive driving as occurring when “an individual commits a combination of moving traffic offenses so as to endanger other persons or property.” More recently NHTSA (2016) replaced the term ‘aggressive driving’ by the more appropriate and comprehensive term ‘risky driving’; still AAA’s conclusion from 2009 holds that almost 60% of deadly crashes are related to “unsafe driving behaviors”. Obviously driving style plays an important role for safety: even if the risky driver himself has fast and reliable control of his own vehicle, he might not leave enough margins for others to react in time or appropriately with their usual control actions.

Zhao et.al. (2020) compare in their very comprehensive study driving styles and driving strategies. They identify four categories of driving strategy: defensive, competitive, negotiated, cooperative. Quantitatively they apply the ‘safe-following-distance’ formula from RSS, and show how these four driving styles use different parameters for a differentiation between safe and unsafe, but there are arguments for all different solutions. Finally, they state as one summary of their study of 165 references “There lacks a rigorous and standardized analysis of safety.”

In summary, there does not seem to be a method available to quantitatively measure safety of driving in traffic with a clear binary limit between *safe* and *unsafe*. A very recent paper by Mattas e.al. (2020) on objective safety measures evaluates physical driving dynamics formulas and shows, that the requirement of ‘surely avoiding a crash’ in car following scenarios with emergency braking leads to a ‘fuzzy’ safety range, equivalent to the safety index spread in our work. A quantitative evaluation of this range leads to an even wider spread than what results from our behaviour-based process of assessing safety. Although developed independently, both papers can help to establish the missing quantitative measure for safety.

For the assessment of human driving skills, driving instructors and examiners take over the task to decide whether a candidate receives a license or not. They finally play an important role in ensuring safety on public roads. Although there are several

hard facts for pass/fail decisions, their assessment is based on the subjective impression of the driving skills of the candidate, monitoring the behavior of the driver in traffic situations (usually without any collision). Many situations in traffic can be judged as more or less safe, and the final decision on issuing the license is based on the overall score for 'acceptably safe' and trust in continuous further improvement.

If a quantitative measure for safe driving in traffic would be available then some ambiguity could be taken out of such decisions. The aim of this paper is to provide a new approach of quantitatively measuring safety which can serve for a similar purpose as a driving examiner, but also applicable to autonomous vehicles. According to the findings in literature, the new method should investigate an approach which does not try to distinguish in a binary way between safe and unsafe, but which uses a continuous score which spans from 'unacceptably unsafe' to 'reliably safe'.

On the impact of supervised driving and driving style feedback

In many countries driving with an experienced driver ('supervised driving', 'graduated licensing') has been established as an additional procedure for fast improvement of the driving skills of young drivers. Although generally insurance rates are higher for new drivers, some insurance companies offer reduced rates for young drivers using supervised driving because this method has proven to reduce accident probability. What happens during this supervised driving phase is not focused on improving collision avoidance skills of the driver, but on avoiding or mitigating of dangerous situations (reducing the exposure to collision-prone situations).

The supervisor helps the unexperienced driver by focusing his attention on early *indicators* of possibly risky situations and unsafe behavior (of the driver or of others). He also might point out, that cooperative behavior would improve traffic flow or reduce risks of collisions. Knowledge of one's own limitations (for example: with respect to fast and correct assessment of situations; available visibility or sensor range; implications of weather conditions on own braking abilities) is another essential part of the support provided by the supervisor.

Automatic feedback on the driving style by a quantitative safety score as proposed in this paper can serve a similar purpose: giving indications for situations which finally

turned out to be risky or unexpected behavior for others, with space for improvement – similar as a benevolent human passenger could do it.

Characteristic parameters assigned to maneuvers

- *Free driving FD* (no vehicle ahead within a 4s temporal distance)
Relevant parameters: speed (e.g. under different weather, lighting, road conditions); speed with a given speed limit; lateral lane position (in relation to lane margins); vehicle dynamics (acceleration, deceleration, lateral acceleration, jerk).
- *Car following CF* (preceding vehicle within 4s temporal distance)
Relevant parameters: speed & relative speed, temporal distance; geometrical longitudinal distance; dynamic changes (time to collision, max. acceleration, max. deceleration, lateral acceleration, jerk); reaction timing on speed changes of the preceding vehicle.
- *Lane change LC* (with cut-out resp. cut-in phases)
Relevant parameters: maneuver speed and duration; longitudinal and lateral lane change acceleration; (temporal and geometric) distance to preceding car at the beginning of the lane change, at time of lane change and to new preceding car at the end; (temporal and geometric) distance and time to collision of the following car on new lane at start and end of lane change; distance, speed and braking deceleration of new follower; distance to end of lane ahead (forced lane change).
- *Overtaking OV* (combination of cut-out and cut-in)
Relevant parameters: all lane change parameters; duration of the complete maneuver; speed variation during maneuver.

Example for a maneuver scoring function

For highway speeds, driving safety depends predominantly on reaction to actions of a preceding car. Thus, a longer *car following* (CF) period has been segmented by one or more response events into separately scored sections. The geometrical and temporal safety distances provide important safety aspects. Even proactive speed reduction

(which might result from realizing brake lights of cars far ahead) before the preceding car starts braking has positive effects on safety. The safety score of the n-th *car following* maneuver is calculated as a weighted average based on the safety indexes c_{si} (for all safety margin parameters i), the indexes c_{bj} (for responsive behavior parameters j) and the indexes c_{mk} (for proactive mitigation parameters k) of the ego vehicle in relation to the lead vehicle:

$$score(CF_n) = \sum_i (w_{si} \cdot c_{si}) + \sum_j (w_{bj} \cdot c_{bj}) + \sum_k (w_{mk} \cdot c_{mk})$$

using respective weights w_{si} , w_{bj} and w_{mk} to balance out the importance of single parameters, with:

$$\sum_i w_{si} + \sum_j w_{bj} + \sum_k w_{mk} = 1$$

Equivalent formulas are used for calculating the other maneuver scores.

Safety score aggregation

Although there are definitively different reasonable ways to aggregate the maneuver scores over time, we used a “ λ -function” to display a real time score for an ongoing driving session. The property of the λ -function can be described easily with the following pseudocode:

λ -function:

Scores = [FD_score, CF_score, LC_score, OV_score]

AggregatedScore = 0

For each Score in Scores:

$\lambda = 0.01 * \text{Duration}(\text{Maneuver}) / 36s$

AggregatedScore = $\lambda * \text{Score} + (1 - \lambda) * \text{AggregatedScore}$

Each element in the Scores list represents a score value of each maneuver performed, and the λ factor represents the impact which controls how fast a previous aggregated score will be overwritten (forgotten) by new incoming scores (λ is chosen to be

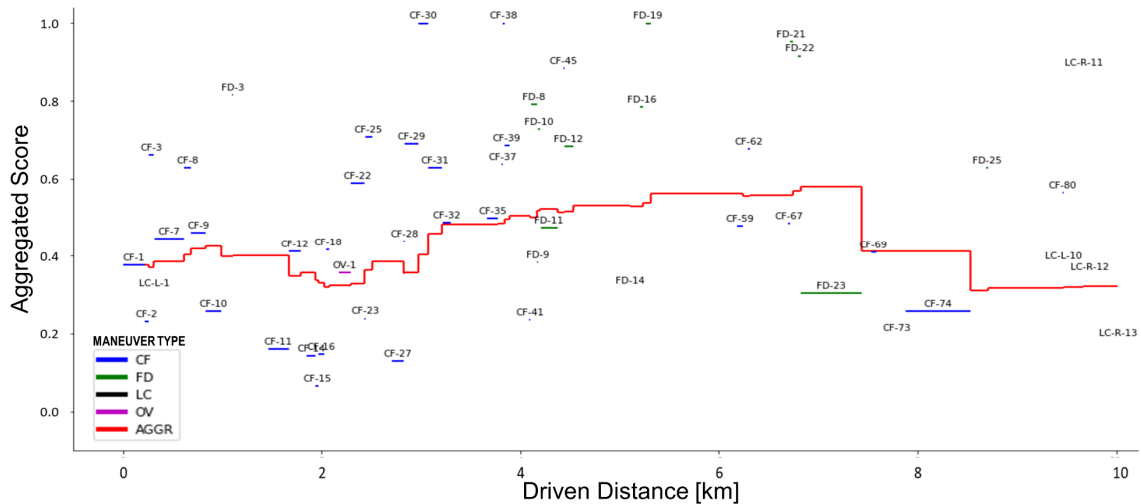


Figure A2. Influence of the maneuver's safety indexes on the development of the score over time (for *risky* driver)

Safety indicators deducted from the maneuvers

Besides the geometrical safety distances, the behavior of the driver in terms of responsiveness and in terms of his mitigation behavior (i.e. proactively avoiding unsafe situations by negative “reaction” times) is used in deriving the safety index for the different maneuvers.

- *Free driving* maneuvers are suitable for deducting unsafe behavior with respect to speed limits. In addition, speeding in curves, unusual forward accelerations or extreme braking accelerations can be seen from the statistics. Bad lane keeping is also detected by an evaluation of lateral position or acceleration statistics.
- *Car following* statistics reveal following distances that are too close (in a temporal or in a geometrical sense), as well as urging, hectic or delayed vehicle maneuvers from the follower car.
- *Lane Change* maneuvers reveal many 'too close' and even endangering driving actions: close approaches before cut-out, choosing insufficient gaps for cut-in, and insufficient time-to-collision values for cut-in into lanes with a different speed.
- *Overtaking* maneuvers reveal differential speeds that are too slow for finishing a take-over in due time (this influences mainly the traffic flow index).

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