DYNAMIC SAFETY ANALYSIS OF LONGITUDINAL MOTION PLANNING FOR AUTONOMOUS VEHICLES

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The main motivations for driving automation of road vehicles lie in safety aspects. Indeed, most road accidents are due to human errors that could be avoided by using driving automation systems. Yet accident rates by unit of distance traveled in conventional traffic are extremely small quantities. The demonstration of safety enhancement by automation of the driving is currently actively debated. Even basic longitudinal motion planning, i.e. adaptive cruise control (ACC) systems, require rigorous demonstration of their safety. Classical linear speed planners are feedback and relaxation processes for the time gap, based on the distance ahead and the speed of the preceding vehicle. Their active safety is tackled thanks to stability analysis. Generally speaking, stability occurs if the relaxation is sufficiently strong. Unfortunately, the acceleration rates and jerks with stable classical speed planners can exceed the bounds recommended by the ISO standard and lead to unsafe dynamics. We propose a novel nonlinear speed planner for ACC systems. The model provides safe and comfortable speed regulations for various driving situations. Reasons are stability properties of the new planner, that hold for any relaxing order. We discuss applications of the car-following model for ACC systems and the robustness of the stability property to mechanical and computational latencies or noise and measurement errors.

Keywords: Autonomous and connected car, Adaptive cruise control, Nonlinear planner, Dynamic safety analysis, Stability analysis, Robustness analysis, Noise and latency.

1. Introduction

Nowadays, the driving automation of road vehicles is going well. Advanced driver-assistance systems (ADAS) allow partial driving automation under driver supervision and in particular driving situation (mainly on highways), while autonomous or self-driving cars start to be tested in real situations (see Verband der Automobilindustrie e.V. (2015a) and Fig. 1). The main motivations for driving automation of road vehicles lie in safety aspects. Indeed, more than 90% of road accidents are attributed to driver errors (among which 41% recognition error, 33% decision error, 11% performance error, 7% sleeping/distracted driver, see Singh (2014)) that could be avoided by using driving automation systems. Other motivation factors for driving automation come from performance and economic arguments (with short-spacing driving, platooning and optimal use of the road networks), or gain of mobility (for children, old persons and persons without driving license) and the development of car share-use models (Litman, 2018).

The driving automation of road vehicles is classically classified in six levels (SAE International, 2018). The automation has no vehicle control at level L0, but it may issue warnings. Level L1 corresponds to assistance systems (e.g. adaptive cruise control, lane keeping). Level L2 is an automation of longitudinal and lateral motion including lane changing for specific situations (mainly on highways). The levels L0, L1, and L2 operate under driver supervision. Further levels are L3 for conditional automation (human driver may have to respond appropriately to a request), L4 for automation in defined use cases and L5 for full automation for all roadway and environmental conditions. The levels L3 to L5 operate without driver supervision and the system is responsible in case of hazard, unexpected events or failures.

Accident rates by distance traveled in conventional traffic are extremely small quantities. Consequently, empirical demonstrations of the safety of autonomous vehicles are difficult to carry out (Kalra and Paddock, 2016). The demonstration of safety enhancement by driving automation without supervision is currently actively debated. Indeed, driving is highly dynamic, and the driving situations are extremely various, especially in urban situations. Exhaustive static listing of all driving situations and hazards in urban and peri-urban contexts at automation levels L3, L4 or L5 are in practice not possible (Bergenhem et al.,

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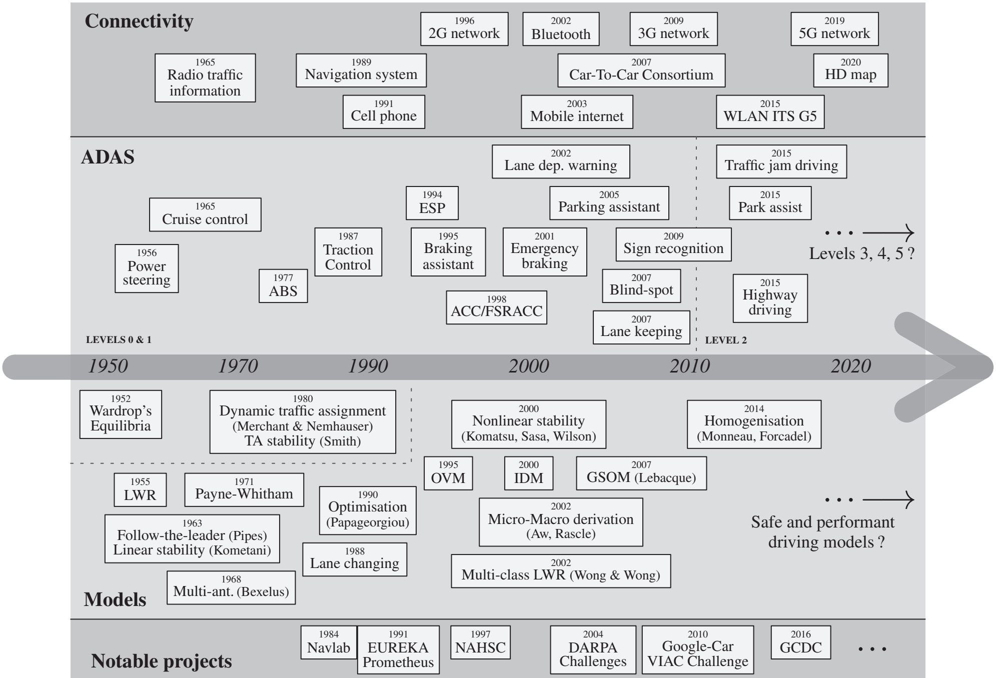

Fig. 1. Historical review for the driving automations : Development of communication tools and networks and driver-assistance systems in the industry in parallel to the development of traffic models and research projects (Verband der Automobilindustrie e.V., 2015a; González et al., 2016).

2015; Koopman and Wagner, 2016; Johansson, 2016) Even basic longitudinal motion planning, i.e. adaptive cruise control (ACC) systems, require rigorous demonstrations of their safety.

In this article, we first highlight the current need for development of dynamic approaches to demonstrate the safety of automated driving. Indeed, the driving is a movement while road traffic is a complex system of interacting agents. The driving automation requires knowledge from complex dynamical systems to demonstrate its safety. We focus then on the longitudinal motion planning of the automated vehicle (i.e. ACC and full speed range ACC systems). We propose a new nonlinear planner and demonstrate active safety by means of stability analysis.

2. Safety analysis for autonomous driving

2.1. *Static safety analysis*

Classical safety analyses of road vehicle components are generally tackled thanks to static approach such as hazard and operability study (HAZOP) or failure mode and effects analysis (FMEA). The functional safety is formulated in the international ISO standard 26262-2,3:2018 (International Organization for Standardization, 2018b) as a completeness and consistency problem. One has for all items and all driving situations to determine for all possible hazards, risk assessments and corresponding functional and technical safety concepts (safety goals, see Fig. 2). The exhaustive listing of potential hazards can be carried out by means of FMEA and classification of the driving situations. For instance, the driving can be classified according to the road (road type, surface type, curving or slope), the vehicle (i.e. speed, direction, state, mode, maneuver), the neighborhood (infrastructure, vehicles, pedestrians, obstacles) or the environment (weather, luminosity, temperature). See Warg et al. (2016); Jang et al. (2015); Verband der Automobilindustrie e.V. (2015b) for detailed classifications.

The Automotive Safety Integrity Level (ASIL) is used to assess and classify the risk of the hazards related to the driving (International Organization for Standardization, 2018b). ASIL classification is a scheme depending on *severity*, *exposure* and *controllability* factors, each of these factors being categorised in different levels. The functional and technical safety concepts recommended

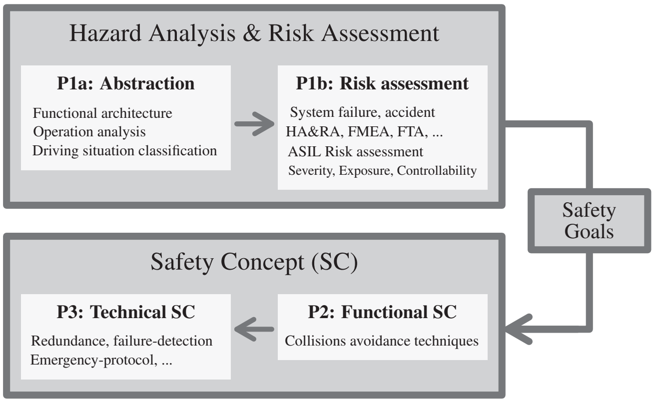

Fig. 2. ISO 26262-2,3 Standard: Definition of technical and functional safety concepts for all possible hazards, item and driving situation (completeness and consistence static problem, International Organization for Standardization (2018b)).

by the ISO 26262:2018 Standard aim to improve the controllability part of the ASIL risk classification (active safety). Possible technical safety concepts for autonomous vehicles are:

- Emergency protocols (e.g., failure detection, emergency braking, emergency avoidance procedure, reactive control, see Binfet-Kull et al. (1998));
- Driving situation analysis (e.g. setting of safe conditions for each maneuver by mathematical criteria based on distances, speeds and kinematic capacity);
- Redundancy (in the sensing: sensor, camera, GPS and map fusion (SLAM), see Dissanayake et al. (2001); Bailey and Durrant-Whyte (2006); in the motion planning: redundant use of several types of planners; in the actuation phase: for instance by steering through stereo-breaking).

Driving situations and potential related hazards are numerous and varied. They can only exhaustively be described in simple conditions, for instance, the driving in highways which consists mainly in following, lane keeping or lane changing situations. Driving situations in urban or peri-urban are more complex. Furthermore driving is highly dynamic and poorly structured. Unsupervised automation systems have to respond appropriately in case of hazards, unexpected events or failures. Yet the exhaustive listing of all driving situations and possible hazards is in practice not possible for the autonomy levels L3, L4 or L5 without driver supervision. Such emphasis is largely debated and investigated in the literature of traffic safety and safety engineering (Warg et al., 2016; Bergenhem et al., 2015; Johansson, 2016; Koopman and Wagner, 2016; Kalra and Paddock, 2016). Indeed autonomous driving requires knowledge from traffic engineering, safety engineering, automation engineering and also from mathematics and physics (see Fig. 3) Systematic methods adapted to dynamical systems under kinematic constraints and dynamic safety analysis have to be developed to demonstrate the safety and reliability of automated driving strategies.

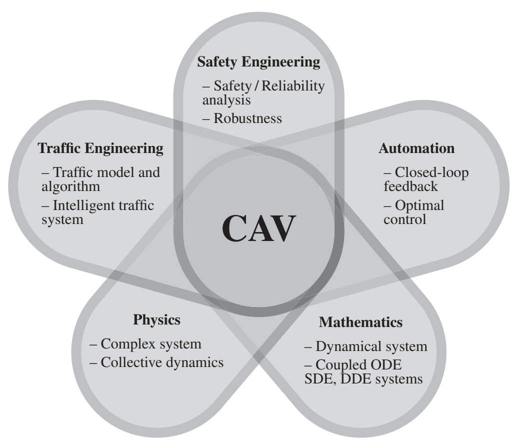

Fig. 3. Connected and autonomous vehicles (CAV) require knowledge from traffic engineering, safety engineering, automation engineering and also from mathematics and physics.

2.2. *Dynamic safety analysis*

Automated vehicles are mission-based and have a functional architecture (Behere and Törngren, 2016; Paden et al., 2016).Classical components of autonomous driving are listed below (see Fig. 4).

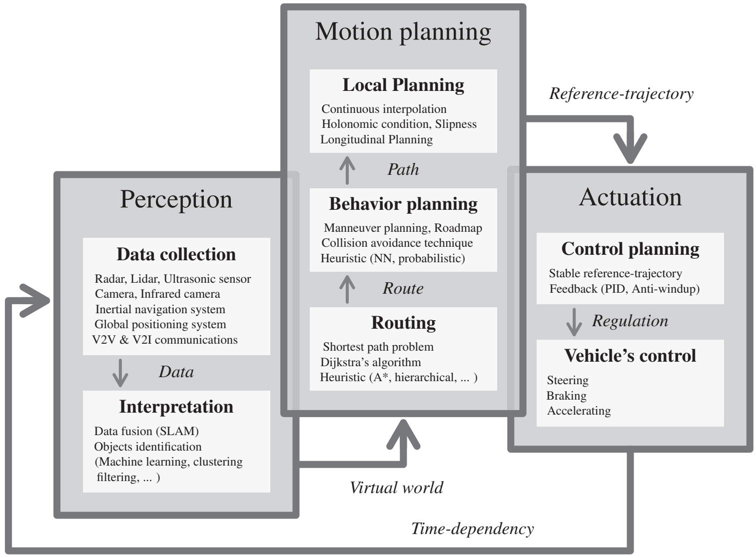

Fig. 4. Illustrative scheme for the functional architecture of automated vehicles. Three mains phases are distinguished: The perception, the motion planning and the actuation. Such steps are repeated into a loop making the system dynamical (Behere and Törngren, 2016; Paden et al., 2016).

(1) The perception phase, consisting in the collection, fusion and interpretation of the sensor (radar, lidar or camera) and communicated (V2V, V2I) data, fusion to high definition map (SLAM), understanding, interpretation and forecast of the driving of situations. Such last step is generally tackled thanks to computational vision, artificial intelligence, and machine learning techniques.

(2) The motion planning phase, operating at strategical (i.e. route choice), technical (maneuver planning) and operational scales (local lateral and longitudinal motion planning). Such plans are generally done thanks to intelligent traffic models and algorithms borrowed from traffic engineering.

(3) The actuation phase, for determination of stable commands for the reference trajectory to follow and the control of the vehicle (steering, braking, and acceleration). Here control techniques by feedback borrowed from automation engineering are used.

The three phases of perception, motion planning and actuation are repeated into loop making the system dynamical. Indeed, the driving automation is a complex dynamical task implying many electronic components, sensors, communication tools and algorithms. The demonstration of the safety of automated driving strategies require systematic approaches and specific tools taking into account for the various dynamical aspects of the driving and the complexity of the architecture. The ISO/PAS 21448:2019 Standard for the safety of the intended function (SoTIF) is especially devoted to such a task (International Organization for Standardization, 2019). Examples of algorithms and methods for the dynamic safety analysis of automated vehicles are

- The stability analysis of the homogeneous streaming and the development of stable and robust collision-free models (Darbha and Rajagopal, 1999; Kikuchi et al., 2003; Zhou and Peng, 2005; Paden et al., 2016);
- The dynamic evaluation of the safety, with e.g. temporal indicators such as Time-to-Collision, Time-to-React or Time-Gap (Tamke et al., 2011; Berthelot et al., 2012);
- The dynamic detection of unusual events or potential conflictual manoeuvres (Lefèvre et al., 2014);
- Real-time trajectory predictions by simulation and model predictive control (MPC) (Falcone et al., 2007; Eidehall and Petersson, 2008; Ammoun and Nashashibi, 2009; Chen and Chen, 2010; Prialé Olivares et al., 2016).

3. Longitudinal motion planning

3.1. *Car-following model*

The longitudinal motion planning of autonomous vehicles in normal driving situations is regulated through adaptive cruise control (ACC) or full speed range ACC (FACC) systems. ACC systems control the acceleration rate and speed of a vehicle according to the distance ahead and the speed of the preceding vehicle (Winner et al., 2015; Paden et al., 2016) (see Fig. 5). The distance is generally measured thanks to radar or lidar sensors, while the speed is obtained by differentiating in time the distance measurements. Two driving situations can be distinguished. The automation systems aim to keep a constant desired speed in the free case when there is no vehicle ahead (cruise control system), while speed and the spacing are simultaneously regulated in the pursuit situation (adaptive cruise control system). In this last case, a classical pursuit strategy consists in keeping a constant time gap $\mathcal{T}$ with the predecessor, the time gap being the distance to the vehicle ahead divided by the current speed. The constant time gap pursuit strategy is the one recommended by the ISO 15622:2018 Standard for ACC and FACC systems (with desired time gap $\mathcal{T}$ varying from 0.8 to 2.2 s, see International Organization for Standardization (2018a)).

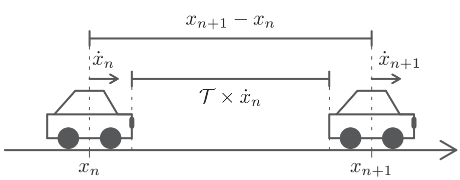

Fig. 5. Main variables for a pursuit situation. The parameter $\mathcal{T} > 0$ is the desired time gap.

Technical kernels of ACC and FACC systems are car-following models. Such a modeling approach is largely developed in traffic engineering. Car-following models are generally second order differential equation systems describing the acceleration rate of a vehicle according to the spacing ahead, the speed and the speed of the predecessor

$$\ddot{x}_n(t) = F\big(\Delta x_n(t), \dot{x}_n(t), \dot{x}_{n+1}(t)\big), \quad (1)$$

with $\Delta x_n(t) = x_{n+1}(t) - x_n(t)$, $x_n(t)$ being the position of the considered vehicle n at time t, while $x_{n+1}(t)$ is the position of the predecessor (see Fig. 5). Classical ACC planners are linear feedback and relaxation processes such as the full velocity difference (FVD) model (Jiang et al., 2001)

$$\ddot{x}_n(t) = \frac{1}{T_1}\left(\frac{\Delta x_n(t) - \ell}{\mathcal{T}} - \dot{x}_n(t)\right) + \frac{1}{T_2}\big(\dot{x}_{n+1}(1) - \dot{x}_n(t)\big), \quad (2)$$

ℓ being the vehicle length and a minimal spacing distance, $\mathcal{T}$ the desired time gap and T_1 and T_2 relaxation times. Nonlinear models such as the intelligent driver model are also used as ACC systems (Kesting et al., 2007; Derbel et al., 2013).

In the adaptive time gap (ATG) car-following model (Tordeux et al., 2010) that we propose for ACC and FACC systems, it is the time gap

$$T_n(t) = \frac{\Delta x_n(t) - \ell}{\dot{x}_n(t)} \quad (3)$$

that is, in accordance to the ISO:15622 Standard, relaxed by a factor λ to the constant desired time gap $\mathcal{T}$:

$$\dot{T}_n(t) = \lambda\big(\mathcal{T} - T_n(t)\big). \quad (4)$$

Supposing that the time gap is not zero, the resulting nonlinear acceleration model is

$$\ddot{x}_n(t) = \lambda \dot{x}_n(t)\left(1 - \frac{\mathcal{T}}{T_n(t)}\right) + \frac{\Delta \dot{x}_n(t)}{T_n(t)} \quad (5)$$

with $\Delta \dot{x}_n(t) = \dot{x}_{n+1}(t) - \dot{x}_n(t)$. The pursuit behavior in transient states (i.e. when the time gap is not the desired time) is controlled for both FVD and ATG models by the relaxation time and factor parameters, the behavior being as smooth as the relaxation is slow. Note that the models may also include a desired (maximal) speed parameter to deal with the free state (cruise control).

3.2. *Stability analysis*

The active safety of ACC and FACC systems is tackled thanks to local and global stability analysis (Darbha and Rajagopal, 1999; Zhou and Peng, 2005; Paden et al., 2016). A single vehicle with assigned speed of the leader is considered for local analysis (see Fig. 6), while a flow of vehicles is investigated for global (or collective) analysis (see Fig. 7). Local over-damped stability conditions

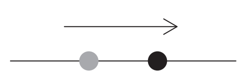

Fig. 6. Scheme for the local stability analysis. A single vehicle with assigned speed of its leader is considered.

allow ensuring collision-free properties of the acceleration planners. Global stability conditions

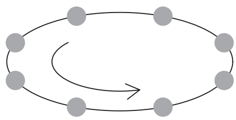

Fig. 7. Scheme for the global (or collective) stability analysis. A flow of vehicles with periodic or infinite boundary conditions is investigated.

guaranty the homogenization of the flow in time and the absence of well-known stop-and-go behaviors (Orosz et al., 2010; Treiber and Kesting, 2013). Stability properties allow to systematically demonstrate the safety of ACC and FACC systems.

Generally speaking, stability occurs if the relaxation is sufficiently strong for both linear and nonlinear models (Darbha and Rajagopal, 1999; Kesting et al., 2007; Kikuchi et al., 2003; Zhou and Peng, 2005; Paden et al., 2016; Derbel et al., 2013). For instance, the local (over-damped) and global stability analysis of the FVD model Eq. (2) are respectively

$$0 < \frac{T_1}{(1+T_1/T_2)^2} < \frac{\mathcal{T}}{4} \tag{6}$$

and

$$0 < \frac{T_1 T_2}{2T_1 + T_2} < \frac{\mathcal{T}}{2} \tag{7}$$

(see, e.g., Treiber and Kesting (2013)). Indeed, the stability conditions constraint the viable domain of the parameters and limit the use of the models.

The ATG model Eq. (5) falls under the exception. The model is systematically over-damped locally and globally stable for any value of the relaxation and desired time gap parameters

$$\lambda, \mathcal{T} > 0. \tag{8}$$

Reasons are the first order relaxation operating for the time gap in the ATG model (see Eq. (4)) that is by construction intrinsically stable. Such property makes the ATG model a robust candidate for ACC and FACC systems.

4. From car-following models to robust ACC systems

Local over-damped and global stability are expected properties for ACC and FACC systems. However, in practice, many factors may affect the stability and generate traffic waves and unsafe behaviors even for stable models. For instance, latency in the automation process induces non-negligible response times. Furthermore, the measurements of the distance and speed are subject to noise, interference or recognition error, especially when the environmental conditions are unfavorable. The challenge for robust ACC and FACC systems lies in improving the stability properties in the presence of latency, uncertainty or again lane changing.

The perception phase, i.e. measurement, interpretation and understanding of the environment, the determination of the reference route, maneuver and trajectory, and the actuation and control of the vehicles, require calculation and application times. Such mechanical and computational response times of the ACC systems, similar in conventional traffic to the reaction time of the driver, are well-known factors of instability. Indeed, a delay in basic models alters the stability resulting in stop-and-go waves (Treiber et al., 2006; Tordeux et al., 2012). Latency-induced instability can be controlled by reducing the delay, for instance using fast algorithms for calculation of the reference trajectory and efficient feedback process in the automation. Connected vehicles and anticipation process including several predecessors in front also allow compensating for the delay and improving the stability (Kesting and Treiber, 2008; Guériau et al., 2016).

The autonomous driving is subject to uncertainties in the measurements of the environment. Such uncertainties are noise, measurement error, or even recognition error, generally due to bad weather conditions, light effects or again interference. Lane-changing (cutting in or cutting out) can also be considered as discontinuous perturbations. Stochastic noise can affect the stability of homogeneous streaming and “kick” a system out of the stable state. Such effects are related as noise-induced stop-and-go waves or sub-critical instability in the literature (Tordeux and Schadschneider, 2016; Treiber and Kesting, 2017). The vehicular dynamics are also affected by kinematic constraints, due e.g. to inertia and limited acceleration and braking capacities, as well as comfort bounds recommended by ISO 15622:2019 Standard (International Organization for Standardization, 2018a).

In summary, the safety analysis of ACC and FACC motion planning systems lies in stability and robustness analysis of delayed stochastic and nonlinear differential equation systems under kinematic constraints. Simple scenarios can be analyzed explicitly by stochastic calculus while real complex situations are generally investigated numerically by simulation.

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References

Ammoun, S. and F. Nashashibi (2009). Real time trajectory prediction for collision risk estimation between vehicles. In *2009 IEEE 5th International Conference on Intelligent Computer Communication and Processing*, pp. 417–422.

Bailey, T. and H. Durrant-Whyte (2006). Simultaneous localization and mapping (SLAM): part II. *IEEE Robotics Automation Magazine 13*(3), 108–117.

Behere, S. and M. Törngren (2016). A functional reference architecture for autonomous driving. *Information and Software Technology 73*, 136–150.

Bergenhem, C., R. Johansson, A. Söderberg, J. Nilsson, J. Tryggvesson, M. Törngren, and S. Ursing (2015). How to Reach Complete Safety Requirement Refinement for Autonomous Vehicles. In M. Roy (Ed.), *CARS 2015 - Critical Automotive applications: Robustness & Safety*, Paris, France.

Berthelot, A., A. Tamke, T. Dang, and G. Breuel (2012). A novel approach for the probabilistic computation of time-to-collision. In *2012 IEEE Intelligent Vehicles Symposium*, pp. 1173–1178.

Binfet-Kull, M., P. Heitmann, and C. Ameling (1998). System safety for an autonomous driving vehicle. In *IEEE International Conference on Intelligent Vehicles*, pp. 469–476.

Chen, S. and F. Chen (2010). Simulation-based assessment of vehicle safety behavior under hazardous driving conditions. *Journal of Transportation Engineering 136*(4), 304–315.

Darbha, S. and K. Rajagopal (1999). Intelligent cruise control systems and traffic flow stability. *Transportation Research Part C: Emerging Technologies 7*(6), 329–352.

Derbel, O., T. Peter, H. Zebiri, B. Mourllion, and M. Basset (2013). Modified intelligent driver model for driver safety and traffic stability improvement. *IFAC Proceedings Volumes 46*(21), 744–749.

Dissanayake, M. W. M. G., P. Newman, S. Clark, H. F. Durrant-Whyte, and M. Csorba (2001). A solution to the simultaneous localization and map building (SLAM) problem. *IEEE Transactions on Robotics and Automation 17*(3), 229–241.

Eidehall, A. and L. Petersson (2008). Statistical threat assessment for general road scenes using monte carlo sampling. *IEEE Transactions on Intelligent Transportation Systems 9*(1), 137–147.

Falcone, P., M. Tufo, F. Borrelli, J. Asgari, and H. E. Tseng (2007). A linear time varying model predictive control approach to the integrated vehicle dynamics control problem in autonomous systems. In *2007 46th IEEE Conference on Decision and Control*, pp. 2980–2985.

González, D., J. Pérez, V. Milanés, and F. Nashashibi (2016). A review of motion planning techniques for automated vehicles. *IEEE Transactions on Intelligent Transportation Systems 17*(4), 1135–1145.

Guériau, M., R. Billot, N.-E. E. Faouzi, J. Monteil, F. Armetta, and S. Hassas (2016). How to assess the benefits of connected vehicles? A simulation framework for the design of cooperative traffic management strategies. *Transportation Research Part C: Emerging Technologies 67*, 266–279.

International Organization for Standardization (2018a). Intelligent transport systems – Adaptive cruise control systems – Performance requirements and test procedures. Technical report, Standard ISO 15622:2018.

International Organization for Standardization (2018b). Road vehicles – Functional safety. Technical report, Standard ISO 26262:2018.

International Organization for Standardization (2019). Road vehicles – Safety of the intended functionality. Technical report, Standard ISO/PAS 21448:2019.

Jang, H. A., H. M. Kwon, S.-H. Hong, and M. K. Lee (2015). A study on situation analysis for asil determination. *Journal of Industrial and Intelligent Information 3*(2), 152–157.

Jiang, R., Q. Wu, and Z. Zhu (2001). Full velocity difference model for a car-following theory. *Phys. Rev. E 64*, 017101.

Johansson, R. (2016). Efficient Identification of Safety Goals in the Automotive E/E Domain. In *8th European Congress on Embedded Real Time Software and Systems (ERTS 2016)*, TOULOUSE, France.

Kalra, N. and S. M. Paddock (2016). Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability? *Transportation Research Part A: Policy and Practice 94*, 182–193.

Kesting, A. and M. Treiber (2008). How reaction time, update time, and adaptation time influence the stability of traffic flow. *Computer-Aided Civil and Infrastructure Engineering 23*(2), 125–137.

Kesting, A., M. Treiber, M. Schönhof, and D. Helbing (2007). Extending adaptive cruise control to adaptive driving strategies. *Transportation Research Record: Journal of the Transportation Research Board 2000*, 16–24.

Kikuchi, S., N. Uno, and M. Tanaka (2003). Impacts of shorter perception-reaction time of adapted cruise controlled vehicles on traffic flow and safety. *Journal of Transportation Engineering 129*(2), 146–154.

Koopman, P. and M. Wagner (2016). Challenges in autonomous vehicle testing and validation. *SAE Int. J. Trans. Safety 4*, 15–24.

Lefèvre, S., D. Vasquez, and C. Laugier (2014). A survey on motion prediction and risk assessment for intelligent vehicles. *ROBOMECH Journal 1*(1), 1–14.

Litman, T. (2018). Autonomous vehicle implementation predictions. Technical report, Victoria Transport Policy Institute.

Orosz, G., R. E. Wilson, and G. Stépán (2010). Traffic jams: dynamics and control. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 368*(1928), 4455–4479.

Paden, B., M. Cáp, S. Z. Yong, D. Yershov, and E. Frazzoli (2016). A survey of motion planning and control techniques for self-driving urban vehicles. *IEEE Transactions on Intelligent Vehicles 1*(1), 33–55.

Prialé Olivares, S., N. Rebernik, A. Eichberger, and E. Stadlober (2016). Virtual stochastic testing of advanced driver assistance systems. In T. Schulze, B. Müller, and G. Meyer (Eds.), *Advanced Microsystems for Automotive Applications 2015*, pp. 25–35. Springer International Publishing.

SAE International (2018). Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems. Technical report, Standard J3016_201806.

Singh, S. (2014). Critical reasons for crashes investigated in the national motor vehicle crash causation survey. Technical report, No. DOT HS 812 115, NHTSA.

Tamke, A., T. Dang, and G. Breuel (2011). A flexible method for criticality assessment in driver assistance systems. In *2011 IEEE Intelligent Vehicles Symposium (IV)*, pp. 697–702.

Tordeux, A., S. Lassarre, and M. Roussignol (2010). An adaptive time gap car-following model. *Transportation Research Part B: Methodological 44*(8), 1115–1131.

Tordeux, A., M. Roussignol, and S. Lassarre (2012). Linear stability analysis of first-order delayed car-following models on a ring. *Phys. Rev. E 86*, 036207.

Tordeux, A. and A. Schadschneider (2016). White and relaxed noises in optimal velocity models for pedestrian flow with stop-and-go waves. *Journal of Physics A: Mathematical and Theoretical 49*(18), 185101.

Treiber, M. and A. Kesting (2013). *Traffic Flow Dynamics: Data, Models and Simulation*. Springer-Verlag Berlin Heidelberg.

Treiber, M. and A. Kesting (2017). The Intelligent Driver Model with Stochasticity – New Insights Into Traffic Flow Oscillations. *Transportation Research Procedia 23*, 174–187.

Treiber, M., A. Kesting, and D. Helbing (2006). Delays, inaccuracies and anticipation in microscopic traffic models. *Physica A: Statistical Mechanics and its Applications 360*(1), 71–88.

Verband der Automobilindustrie e.V. (2015a). Automation – From Driver Assistance Systems to Automated Driving. Technical report, VDA Magazine – Automation.

Verband der Automobilindustrie e.V. (2015b). Situationskatalog E-parameter nach ISO 26262-3. Technical report, VDA 702.

Warg, F., M. Gassilewski, J. Tryggvesson, V. Izosimov, A. Werneman, and R. Johansson (2016). Defining autonomous functions using iterative hazard analysis and requirements refinement. In A. Skavhaug, J. Guiochet, E. Schoitsch, and F. Bitsch (Eds.), *Computer Safety, Reliability, and Security*, pp. 286–297. Springer International Publishing.

Winner, H., s. Hakuli, F. Lotz, and C. Singer (2015). *Handbuch Fahrerassistenzsysteme*. Springer Vieweg.

Zhou, J. and H. Peng (2005). Range policy of adaptive cruise control vehicles for improved flow stability and string stability. *IEEE Transactions on Intelligent Transportation Systems 6*(2), 229–237.