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Experimental analysis of road characteristics' impact on the performance of lane support system

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Abstract

The development and integration of automated driving systems in vehicles hold substantial promise for fostering enhanced efficiency, environmental sustainability, and safety in transportation. Notably, at the lower levels of automation (L1, L2), the lane-keeping system emerges as a widely adopted automated driving feature, ensuring the vehicle's alignment within its designated lane. With the recent introduction of new European regulations mandating the inclusion of emergency lane-keeping systems in all new vehicles starting July 2022, a growing prevalence of such systems is anticipated in the forthcoming decades.
The precision and reliability of these systems in accurately detecting road markings and their distinctive features are paramount for achieving safe and intelligent mobility solutions. To fully capitalize on the advantages these systems offer, they need to expand their operational design domain. This necessitates a comprehensive understanding of their performance across diverse road design and maintenance conditions, supporting road operators in updating standards and maintenance protocols.
The primary objective of this study is to investigate how various road characteristics impact the performance of lane-keeping assistant systems. Within this framework, the paper presents an experimental evaluation of Lane-Keeping System (LSS) performance conducted on two-lane rural roads. Advanced technologies for road monitoring and LSS were employed under different road and driving conditions.
Through rigorous data analysis and the application of statistical models, variables significant to the fault probability of LSS were identified, highlighting the role played by horizontal curvature and driving speed. Results underscore the relevance of horizontal curvature as a critical factor constraining the physical infrastructure, shaping the operational design domain of LSS. This research contributes valuable insights toward optimizing lane-keeping assistant systems, thereby advancing the development and deployment of safe and efficient automated driving systems in diverse road scenarios.

Keywords – Automated Driving System, Lane Support System, Road Safety, Road Geometry, Road marking, Speed

1. Introduction

Vehicle automation has the potential to enhance driving ease and safety, offering opportunities for improved overall safety and mobility. Despite the significant potential benefits, obstacles to mass-market penetration persist, particularly concerning the establishment of appropriate standards for liability and guidelines for certifying autonomous vehicles [9].

According to the SAE Standard J3016 definition [14], driving automation progresses through five stages, ranging from driver assistance (Level 1) to fully automated vehicles (Level 5), with an additional level indicating no automation (Level 0). The most advanced technologies currently available, such as SAE level 2 "partial automation," are prevalent on the market, and starting in 2022, specific safety technologies will be mandated in new European vehicles. These mandatory safety features include Lane Support Systems (LSS), capable of detecting impending lane drifting and alerting the driver through haptic, visual, and audible methods (Level 1), or actively steering the vehicle back into the lane (Level 2).

From a safety perspective, assuming the system is 100% reliable, LSS at levels 1 and 2 can be likened to rumble strips, which, based on years of data, have demonstrated safety effectiveness in reducing severe lane drift crashes by approximately 30%. Notably, rumble strips address all vehicles at the treated site, while in-vehicle systems only apply to the equipped vehicle. However, LSS provides the advantage of issuing warnings for lane drifting at all locations. Conversely, LSS performance may be compromised by system malfunctions resulting from internal factors or faults arising from road characteristics (e.g., marking quality) and environmental factors (e.g., light, weather). A recent study [15] has estimated crash prevention based on varying rates of LSS effectiveness, ranging from 20% to 100%, yet road factors influencing LSS effectiveness remain undefined due to the absence of relevant literature.

At levels 3 and 4, the role of LSS becomes more critical, as a system fault during navigation could lead to disengagement of the automation, with the critical phase requiring a fallback to the driver. In this context, the paper aims to enhance understanding of LSS performance and the probability of faults, with a particular emphasis on exploring the effects of horizontal alignment.

2. Technology framework

The sensory components of automated driving necessitate the collection of data and information by an automated vehicle before it can make informed decisions. Fully automated driving at Levels 4 or 5 entails the use of multiple sensor systems, including cameras, radar, Light Detection and Ranging (LIDAR), the Global Navigation Satellite System (GNSS), and redundant connectivity features. Currently, camera and radar systems are integral to Levels 1 and 2 automation and serve as prerequisites for higher automation levels. Mono- and stereo cameras [1], in conjunction with radar systems, provide precise evaluations of speed, distance, obstacle outlines, and moving objects.

Radar sensors, operating at short (24 GHz) or long (77 GHz) range, are positioned at the front and rear of the vehicle to monitor traffic, with the ability to detect objects at distances ranging from centimeters to several hundred meters. However, radar detection can be susceptible to disturbances from electromagnetic and metallic artifacts. LIDAR systems, increasingly utilized for obstacle detection, navigable space identification, and Simultaneous Localization and Mapping (SLAM), now include advanced multiple-layer laser sensors, such as "SCALA" by Valeo and IBEO. These LIDAR sensors meet automotive specifications for long-distance obstacle detection and SLAM but generate a substantial amount of data, limiting real-time embedded application usability [11]. Additionally, laser scanners are susceptible to environmental conditions such as dirt, snow, and heavy rain.

Radar, LIDAR, GNSS, and cameras, combined with high-definition maps, enable automated vehicles to navigate, identify and avoid obstacles, and interpret road markings and traffic signs.

Inertial Navigation Systems (INS) further enhance positioning accuracy by combining GNSS data with correction services and other sensors like odometers and Inertial Measurement Units (IMUs).

For Levels 3 and beyond, connected and autonomous vehicles (CAVs) require precise navigation systems for accurate positioning within centimeters on highly detailed three-dimensional maps, necessitating continuous updates, especially in complex traffic environments like intersections [16] [21]. However, generating such maps poses challenges due to the vast amount of data required and the availability over the whole road network. Furthermore, the development of artificial intelligence (AI) systems for map creation is still evolving, and privacy concerns add another layer of complexity to high-definition (HD) map creation.

Regarding vehicle-to-infrastructure communication (V2I), two approaches are distinguished [19] [9]: smart infrastructure with a non-intelligent vehicle and non-intelligent infrastructure with an intelligent vehicle. In the latter case, the concept of adding cooperative elements later is favoured, particularly in the United States [8].

When road infrastructure interpretation lacks strong connectivity support, camera-based machine vision emerges as the predominant sensor system for reading markings, signs, and traffic signals. While other sensors and technologies, such as LIDAR, high-definition maps, and GNSS, can support this function, their full availability is delayed due to implementation costs and the need for a comprehensive digital infrastructure with adequate network coverage (4/5G). Future research on the direct perception approach may alter perception technology requirements, potentially shifting towards increased reliance on vision-based perception and reduced demand for highly detailed a priori information like GNSS localization and HD mapping [20].

Machine vision for CAVs involves cameras and sensors feeding digital data to a signal processor, and running complex AI algorithms for control [10]. Forward-facing cameras, with medium to high sensing ranges, employ algorithms to detect and classify objects, determining the CAV's distance from them. Current camera systems use CMOS image sensors with resolutions of up to two megapixels, requiring high dynamic range, light intensity, and frame rate. The contrast between pixels in pavement markings and the road is crucial for pavement marking detection [18].

3. Data collection

Open-road testing on public roads provides a real-world laboratory environment for testing and evaluating Automatic Driving Systems (ADS). This approach complements and validates closed-track and Modeling and Simulation (M&S) testing while exposing systems to a diverse range of real-world conditions. The physical infrastructure and environmental conditions encountered during open-road testing are crucial attributes for defining the Operational Design Domain (ODD) of an ADS.

However, open-road testing, when compared to closed-track testing, comes with certain drawbacks, including:

- Lack of controllability: Public road scenarios offer limited control over ODD conditions.
- Lack of replicability: Replicating public road scenarios precisely in different locations is challenging.
- Lack of repeatability: Repeating public road scenarios exactly over multiple iterations is difficult.
- Safety and legal liability: Testing Connected and Autonomous Vehicles (CAVs) on public roads requires specific national-level legislation governing the testing and deployment of ADSs.

To address controllability, replicability, and repeatability issues, we employed a longitudinal approach in the experimental setup. Repeated runs were conducted in selected sections of two-lane rural roads with low traffic volume and physical conditions were identified in real-time by a mobile laboratory during the test. Additionally, to comply with safety and legal constraints, the Lane Support System (LSS) operated during the test but did not assume the Dynamic Driving Task (DDT), which remained under the control of the human driver. The system output used for driver warning (Level 1) or required for the DDT at Level 2 and above was recorded using a custom Arduino platform and software.

The Automatic Road Analyzer (ARAN) [2] [3] was used to obtain measures of the road's geometric characteristics, including cross-section, gradients, and horizontal and vertical alignments.

HD images captured by three cameras provided centimeter-precise information about lane widths, shoulders, verges, and markings. The horizontal alignment, such as curve radius, was extracted by interpolating the vehicle position with sub-meter precision, independent of the satellite's views of the GPS receivers.

For this study, the ARAN acquisition equipment was combined with a Mobileye 6.0 system [12], featuring a digital camera located on the front windshield inside the vehicle (Fig. 1). This Mobileye equipment, representing the state-of-the-art in vision-based ADS, is widely used by car manufacturers, including Audi, Mercedes-Benz, and Volvo, for their semi-autonomous applications [20].

Fig. 1 Mobileye 6 – in-vehicle installation

Within the Mobileye camera, the EyeQ2® image processing chip plays a pivotal role, executing high-performance real-time image processing for vehicle, pedestrian, and lane detection. It also calculates dynamic distances between the vehicle and road objects [12]. In the market configuration, alerts are conveyed to the driver through the EyeWatch® display.

For the present study, the focus was solely on the lane departure warning (LDW) feature. This feature triggers a visual and audio alert when a lane deviation occurs at speeds exceeding 35 km/h. It refrains from issuing warnings when the speed is below the set threshold of 35 km/h, the direction indicator is active, or the lane delimitation strips are either not traced or traced inaccurately. The lane markings observed were in good condition, characterized by a coefficient in diffuse illumination (Qd) exceeding 100 mcd/m²/lx [7].

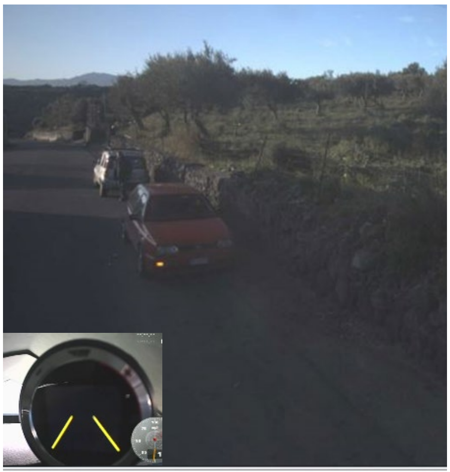
To facilitate more comprehensive data collection, the output from the warning system, utilizing the Mobileye Standard CAN protocol, was recorded. Synchronization with ARAN data was achieved by constructing an Arduino platform and developing codes in the C language. Specifically, LDW fault events were classified into LDW not available (LDW=1) and LDW available (LDW=0), with their positions synchronized with the ARAN GPS (Global Positioning System) system.

4. Results

Multiple runs were conducted under dry and daylight conditions in order to record at least four different speeds for each road section, resulting in data collection of 1934 samples (Table 1). A two-lane rural road was deliberately chosen for its more constrained conditions compared to primary rural roads, encompassing aspects such as road characteristics (e.g., minimum curve radius, lane and shoulder widths) and maintenance conditions (e.g., marking and pavement distress).

All collected data were standardized to homogeneous sections, with a minimum and maximum length of 20 m and 65 m, respectively. These sections maintained a consistent value for each variable considered in the experiment. The chosen range for minimum and maximum section lengths aimed to ensure a travel time between 1 and 6 seconds, accounting for the spectrum of running speeds. This duration was deemed optimal for recording reliable Lane Support System (LSS) outputs and fault conditions presenting potential hazards for driving assistance.

Factors external to the experimental setup, such as parked vehicles and edge pavement drop-offs, which could introduce artefacts, were identified through a thorough review of video recordings captured by an auxiliary front camera (Fig. 2). Subsequently, these factors were eliminated from the database to enhance the overall accuracy and reliability of the collected data.



Missing marking detection due to parked vehicles (false LDW off)

Road edge detected as marking (false LDW on)

Fig. 2 Artifact detection for data cleaning

Tab. 1 presents the summary statistics for the variables contained within the database.

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
1/R	1934	0.000000	0.02211166	0.0024230	0.003313750
Average Speed	1934	35	84	55,81	10,873
Section length [m]	1934	20.00	65.00	39.264	5.167

Tab. 1 Summary Statistics

The considerable variability in the selected speeds across different runs, as illustrated in Fig. 3, led to a low correlation between curvature radius and running speed. This is further evidenced by the minimal value of the Pearson coefficient, as indicated in Tab. 2.

		1/R	Average Speed
1/R	Pearson Correlation	1	-0.209
	Sig. (2-tailed)		0.000
	N	1934	1934

Tab. 2 Pearson correlation between 1/R and Speed

Regarding the Mobileye data, the Lane Departure Warning (LDW) fault occurs when the system is unable to detect the line marking, resulting in a loss of detection.

The average overall percentage of LDW faults during the test was approximately 2.12%.

Fig. 4 illustrates a threshold value of curvature radius at around 200 m, below which the majority of Lane Support System (LSS) fault events can be observed.

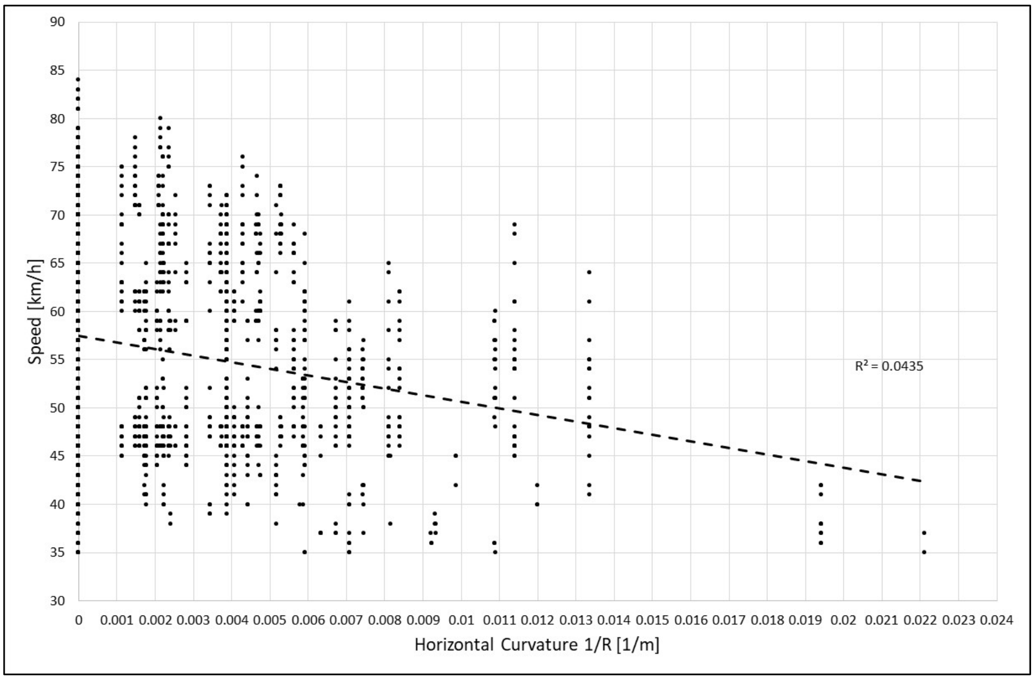


Fig. 3 Variability of speed vs. horizontal curvature

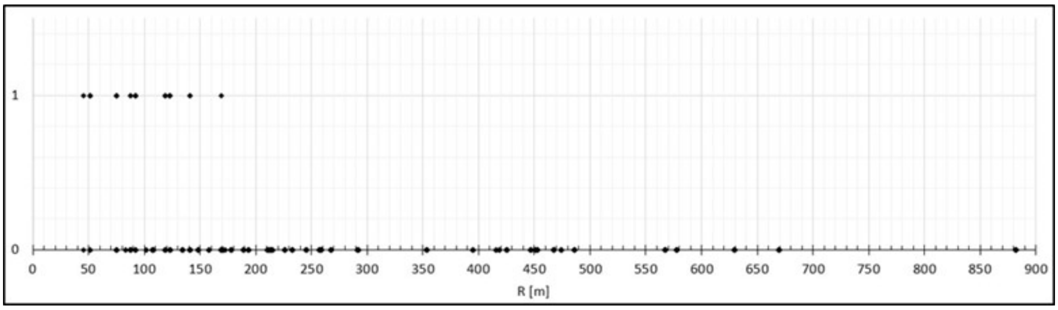


Fig. 4 LSS fault (value=1) vs. horizontal curvature

For curvature radii less than 200 m, the probability of Lane Departure Warning (LDW) faults increases to 7.8%, compared to 0.88% in sections with higher radii, including tangents (refer to Tab. 3).

	LDW fault Category	Sample size N	Observed	
			LDW Faults	Proportion
R≤200 m	= 1	346	27	7.80 %
R>200 m	= 1	1588	14	0.88 %

Tab. 3 Pearson correlation between R and Speed

Conversely, Fig. 5 illustrates the dispersion of Lane Departure Warning (LDW) fault events across a broad range of speeds, predominantly below 71 km/h. This pattern is primarily observed in tests conducted in curved sections at various speeds, as depicted in Fig. 3.

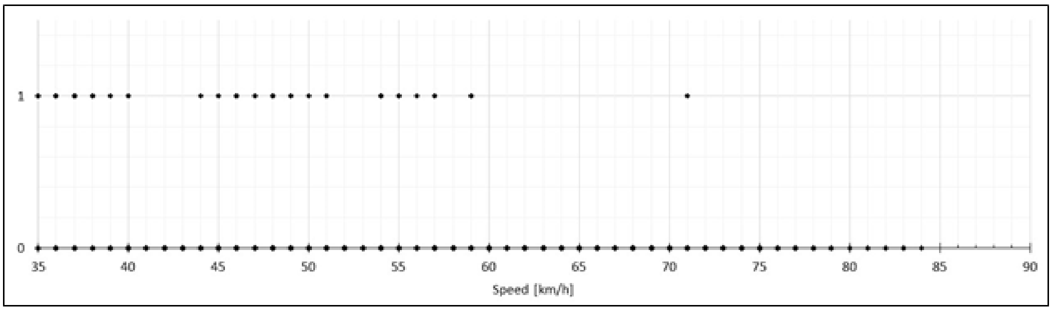


Fig. 5 LSS fault (value=1) vs. speed

A binomial random variable, such as the Lane Departure Warning (LDW) on/off status, can be viewed as the sum of a fixed number of independent Bernoulli trials. Bayesian Inference for Binomial distributions offers a valuable tool for estimating confidence intervals for this type of fault probability. The parameter of interest is the probability π of success in a fixed number of trials that may result in either success or failure. Importantly, each trial is independent, and the probability π remains constant across all trials.

In the specific case of employing the standard uniform distribution as a non-informative prior (Beta: alpha =1, beta =1), Bayesian inference involves characterizing the posterior distribution based on observed data and subsequently constructing credible intervals to make direct inferences.

The Bayesian Inference for Binomial distributions revealed a notable distinction at a 95% significance level between the two distributions of LDW fault probability for curvature radii less than or equal to 200 m and those greater than 200 m (as shown in Tab. 4).

Posterior Distribution Characterization for Binomial Inference [a]					
	Posterior			95% Credible Interval	
	Mode	Mean	Var.	Lower Bound	Upper Bound
R≤200	0.078	0.080	0.000	0.054	0.111
R>200	0.009	0.009	0.000	0.005	0.015
a. Prior on Binomial proportion: Beta(1, 1).					

Tab. 4 Bayesian One Sample Inference for Binomial distributions in two different classes of curvature

In the case of curvature radii less than 200 m and greater than 70 m, the speed is nearly uniformly distributed within the range of 35-71 km/h, with an average speed of 51 km/h (as depicted in Fig. 3). Analyzing the 334 curved sections, dividing them into two speed classes—speeds less than or equal to 51 km/h and speeds greater than 51 km/h (refer to Tab. 5)—the posterior distributions of Lane Departure Warning (LDW) faults exhibit notably similar fault probabilities. There is a clear overlap in the confidence intervals, signifying comparable fault probabilities for both speed categories (see Tab. 6).

			Observed	
	LSS fault Category	Sample size N	LSS Faults	Proportion
V≤51 km/h	= 1	172	11	6.4 %
V>51 km/h	= 1	162	10	6.2 %

Tab. 5 Bayesian One Sample Inference for Binomial distributions in two different classes of speed

Posterior Distribution Characterization for Binomial Inference[a]					
	Posterior			95% Credible Interval	
	Mode	Mean	Var.	Lower Bound	Upper Bound
V≤51 km/h	0.064	0.069	0.000	0.036	0.111
V>51 km/h	0.062	0.067	0.000	0.034	0.110
a. Prior on Binomial proportion: Beta(1, 1).					

Tab. 6 Bayesian One Sample Inference for Binomial distributions in two different classes of speed

5. Conclusions

This paper outlines the findings of an experimental study, focusing on a meticulous data collection of Lane Departure Warning (LDW) faults within sections of two-lane rural roads characterized by varying curvature radii and well-maintained lane markings. The primary objective is to underscore the pivotal role of horizontal alignment in influencing the performance of Forward Vision-based Driver Assistance Systems. The results of this study serve to complement existing knowledge, particularly emphasizing the significance of pavement marking characteristics in defining the Operational Design Domain (ODD) for Lane Support Systems (LSSs). Essential features such as viewing geometry and viewing angle within the image processing algorithm are crucial for detecting road lane markings, especially in curved road alignments. Previous studies [4] [13] have highlighted the curvature radius and marking coefficient Qd as the most relevant road factors explaining LSS fault probability. Thresholds of Qd>150 mcd/m2/lx and R>140 m have been identified under Day and Dry testing conditions. In different environmental conditions (wet pavement, heavy rain), another study [14] highlighted the relevance of reflectivity value in wet conditions (RLw) and confirmed the importance of horizontal curvature in defining the Operational Design Domain (ODD) for Lane Support Systems (LSS).

This study affirms the 200 m radius as a critical threshold for LDW performance, showcasing an escalation in fault probability from approximately 1% to about 8%, in daylight and good pavement marking conditions. The curvature radius of 200 m, particularly at varying running speeds, emerges as a significant geometric constraint in rural two-lane road networks, especially in mountainous regions where curves with a radius less than 200 m and wide deflection angle are commonplace. The horizontal curvature warrants increased consideration in LSS testing and development, particularly in sharp curves prevalent in secondary roads and specific locations like intersections, interchanges, and roadwork areas.

Interestingly, the speed variability in curved sections does not exhibit significant effects in explaining system faults within the tested scenarios.

While the Mobileye equipment utilized in the experiment represents the current state-of-the-art in vision-based systems, it is acknowledged that different systems may yield diverse results based on varying AI algorithms and camera systems. Nevertheless, the experiment's results underscore horizontal curvature as a specific road factor influencing LSS, emphasizing the need for its identification in defining certification testing procedures and the Operational Design Domain of the system.

Ensuring the safe and widespread integration of Autonomous Vehicles (AVs) on public roads requires a clearly defined ODD for these systems which should include also other factors related to the “Scenery” of the road infrastructure, the “Environmental Conditions” and the “Dynamic Elements”, as detailed listed in ODD taxonomy for an automated driving system [5]. A shared responsibility between the public sector and Original Equipment Manufacturers (OEMs) is vital. Road agencies are called upon to maintain infrastructure conditions at optimal standards, while ongoing technological development of LSSs is imperative to expand the ODD and address the geometric features of existing roads effectively.

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