Sight Distance of Automated Vehicle Considering Highway Vertical Alignments and Its Implications for Speed Limits

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Abstract

Most existing road infrastructures were constructed before the emergence of automated vehicles (AV) without considering their operational needs. Whether and how AV could safely adapt to as-built highway geometry remain inconclusive, and a plausible concern is a challenge from vertical alignments. To fill this gap, this study uses virtual simulation to investigate the available sight distance (ASD) for AV on vertical alignments subject to the current highway geometric design specification, and its implications for speed limits. According to the scenario generation framework, several scenarios featuring vertical geometric elements and the light detection and ranging (LiDAR) sensor were created and tested. Moreover, the maximum speed for adequate ASD is calculated to determine the AV speed limit, considering safe sight distance and speed consistency requirements. The results indicate that crest curves are not disadvantaged in ASD compared with either the sag curves or tangent grades. Only equipped with multi-channel LiDAR and advanced perception algorithms enabling a lower detection threshold, would Level 4 AV be compatible with the as-built vertical alignment with a design speed ($V_d$) of 100 km/h. However, Level 3 AV can only adapt to the vertical profile with $V_d = 60$ km/h. The findings of this study should be of interest to the road-oriented operational design domain and support road administrators in regulating AV safe speeds.
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Index Terms—automated vehicle; available sight distance; safe speed; vertical alignment; virtual simulation;

I. INTRODUCTION

The International Society of Automotive Engineers (SAE International) has classified driving automation into six levels [1], i.e., from No Driving Automation (level 0, L0) to Full Driving Automation (level 5, L5). Over the past few years, many features of lower automation levels have been available in the market (e.g., L2 Tesla). In the meantime, many elements of higher levels have been tested on public roads (e.g., L4 Baidu). According to the China automobile market statistics report [2], general automation is developing from L2 to L3. In other words, it is maturing from advanced driver assist systems to Automated Driving Systems (ADS).

Recent studies have revealed significant differences in the performance and features between automated vehicles (AV, i.e., vehicles equipped with ADS) and traditional human-driven vehicles (HV), particularly in the perception-related function (e.g., [3,4]). However, most as-built road infrastructures, especially road geometry, were designed entirely considering the characteristics of human drivers or HV [5]. In this regard, the compatibility of AV with as-built roads is gaining increasing interest from academia and industry.

As stated in previous studies (e.g., [6]), specifying the operational design domain (ODD) of AV is essential to deploy them on as-built roads safely. The ODD refers to AV’s needed operating conditions, including environmental, traffic, and roadway characteristics [1]. However, only less detailed ODD requirements were specified, such as merely mentioning the allowable road type without the speed limit for the specific geometric conditions. This might cause consumers’ over-reliance, suspicion, or confusion [7,8]. In addition, it is very challenging to address a lack of ODD standardization or elaborate on numerous conditions for every vehicle [9]. These limitations hinder road administrators’ application of this vehicle-based ODD concept for road design, management, and maintenance.

Since many road infrastructures were constructed before the AV emergence, it could be cost-effective for road administrators to adapt AV to the as-built roads. Therefore, adjusting or improving the ODD concept from the road perspective is needed. That is, offering such a road-oriented ODD concept by stating the specific road condition (e.g., road geometry) and its matching AV operation (e.g., driving speed). As García et al. [9] proposed, the road-oriented ODD concept can be defined as the operational road section. Previous studies focused mostly on horizontal alignments. They (e.g., [10]) highlighted the perception-related limitation of AV and justified the available sight distance (ASD) for exploring AV’s compatibility. Given the limited angular resolution, range, and object detection threshold of AV sensors, AV might not have sufficient ASD to ensure safe driving at high speeds on horizontal curved roads.

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Vertical alignments may be subject to the same concerns as horizontal alignments due to vertical curves. Although Wang et al. [10] demonstrated that either a higher sensor mounting height or a larger upward vertical field of view (VFoV) would induce a milder requirement of vertical alignments for AV, sightline obstructions might be caused by the crest and sag-curve pavement profile, as depicted in Fig. 1. Such obstructions reduce ASD and the corresponding maximum safe speed [11-13]. However, the results on vertical alignments were quite inconclusive. Only a limited number of scenarios including crest vertical curves and advanced driver assist systems were investigated by field tests [11]. In addition, the analytical studies (e.g., [10]) might overestimate the actual AV’s perception ability since some critical sensor-related factors (e.g., angular resolution) were not considered. Given those motivations and limitations, further extending road geometry studies to vertical alignments is vital.

This study investigates whether and how AV could safely adapt to as-built vertical alignment. In this regard, two intriguing questions arise: how far can AV see, and how fast shall it drive? A series of virtual simulations featuring the AV and vertical alignment was conducted to estimate ASD. Based on that, we derived the maximum speed for adequate ASD ($V_{max}$) according to the safe sight distance (SD) requirement. That is, ASD shall not be less than the required stopping sight distance (RSD) [14]. In addition, the $V_{max}$-based speed limit on the road sections was determined considering speed consistency. Note that the road type in this study refers to the highway, as only the ego vehicle and geometric road features were considered. The present study offers thorough and feasible answers to these two questions that are expected to advance the road-oriented ODD further and support road administrators in regulating AV’s safe speeds on as-built vertical alignments.

The study is organized as follows. Section 2 presents the literature review. Section 3 introduces the simulation design. Section 4 presents the simulation and analysis results, and Section 5 presents concluding remarks, limitations, and future work.

II. LITERATURE REVIEW

A. Related Work

Over the past few years, many efforts in the literature have been expended on improving the ODD concept from the road side and determining how AV could safely adapt to the as-built roadway geometry. Recent studies can be classified into four types: analytical studies, empirical studies, computer-aided studies, and virtual simulation studies.

The analytical studies determined the required geometric design controls (e.g., vertical alignment) or ODDs (e.g., sensor range) for AV [3,4,10,11,15-18]. However, they merely considered perception sensors' simple two-dimensional field of view (FoV) or mounting heights, omitting other critical technical parameters (e.g., angular resolutions) and object detection thresholds. That might overestimate the actual AV’s perception ability from the roadway geometry perspective (i.e., ASD) and thus ease the geometric requirement or ODD.

The empirical studies better capture the AV's natural characteristics [11,19,20]. These studies investigated maximum operational speeds for the automation system on public roads. Such field tests, although having real alignment conditions, are difficult to completely exclude the effect of non-geometric factors (e.g., traffic flow and weather). In addition, those costly tests would limit the sample sizes regarding various sensor configurations and geometric design elements.

The computer-aided studies use actual LiDAR point cloud data on highways [12,21]. These studies created a simulation environment and then proposed automatic ASD estimation algorithms. Compared with analytical and empirical studies, computer-aided studies increase the FoV from two dimensions to three, save testing time, and expand the sensor-related sample size (e.g., sensor quantity). Nevertheless, they failed to consider other sensor-related factors (e.g., angular resolution). Also, the sensitivity investigation of geometric conditions might be insufficient due to the limited number of road scenarios modeled by the point clouds.

The virtual simulation studies avoid the abovementioned issues and limitations [13,22]. These studies adopted a high-fidelity simulation technology to simulate AV’s perception process effectively and thus estimated ASD along different alignments. Importantly, they have ascertained that LiDAR's angular resolutions and laser-point thresholds for object detection substantially affect ASD. Moreover, this method is well-recognized in the AV-testing domain [23]. It can customize numerous scenarios effectively, which include road geometry, sensors, AV features, etc.

B. AV’s LiDAR-based Perception System

The LiDAR-based multi-sensor fusion and perception system has been recognized as one of the optimal perception solutions for AV because of LiDAR’s advantages over the camera and radio detection and ranging (Radar) sensor [24]. Generally, the camera is more susceptible to adverse weather and lighting conditions [25]; the Radar has a narrower FoV, especially the VFoV, a shorter range, a coarser angular resolution, and inferior performance on stationary target detection [26].

As stated above, the ASD of AV is a critical item in previous studies, which can effectively reflect the safety margin provided by the alignment from the SD perspective and instruct AV’s safe driving speeds [27]. The ASD refers to the longest path distance at which a stationary obstruction along the roadway geometry...
can be detected. As demonstrated by Wang et al. [13,22], the primary cause of many crashes involving an AV colliding with a stationary obstruction is ASD < RSD. Furthermore, in the case of ASD testing, sensing results from a LiDAR would play a priority role over those from either a camera or a Radar mainly due to the two features of ‘long-distance’ and ‘stationary obstruction’, respectively.

Therefore, the AV in this context refers to an AV equipped with the LiDAR-based perception system (LAV). Note that effective object detection is closely related to a sufficient number of laser points impinging on that object, as highlighted in previous studies (e.g., [22]).

III. METHODS

A. Overview

The workflow of this study is shown in Fig. 2. First, a co-simulation platform is used to conduct virtual simulations. Then, the experiments are designed according to the basic framework of AV driving scenario generation (i.e., functional-logical-concrete scenarios), as defined in the PEGASUS project [28]. Those experiments consider vertical alignments and LiDAR elements. The vertical alignment elements are design speed (\(V_d\)), length and curvature of crest curve (\(L_{CV}, R_{CV}\)), length and curvature of sag curve (\(L_{SV}, R_{SV}\)), and tangent grade length (\(L_{TG}\)). The LiDAR elements are the number of vertical channels (\(N_v\)), laser point threshold for vehicle detection (\(N_T\)), and mounting height (\(h_{ml}\)). After testing each trial, the ASD of LAV is output. Second, ‘how far can LAV see on highway vertical alignments?’ is answered by investigating the relationships between ASD and those variables. With the output of ASD, ‘how fast shall LAV drive on highway vertical alignments?’ is further addressed by setting the ASD equal to the RSD of LAV. The outcome is \(V_{\text{max}}\) for LAV. Finally, given a specific vertical alignment, a \(V_{\text{max}}\) consistent with \(V_d\) in terms of that alignment is adopted as the speed limit.

![Fig. 2. Proposed workflow.](image)

B. Simulation Platform

As shown in Fig. 2, we used the PreScan® software package (version 2021. 1.0) and MATLAB/Simulink (version 2018b) to establish the co-simulation platform. This platform is good at physics-based calculations of perception sensor inputs/outputs. It is highly effective on simulations of roads, vehicle control, and AV systems [29], which has been employed in previous studies to investigate ASD of LAV (e.g., [22]).

Specifically, PreScan can offer a colossal actor database of vehicles, user-defined vehicle trajectories, roads with varied geometric characteristics, and top-notch sensor models [29]. MATLAB/Simulink enables real-time data access from PreScan through a cluster communication port-based interface. The data herein include LiDAR outputs (e.g., the number of received laser points) and the vehicle’s path information (e.g., relative path distance). Based on these data, the ASD calculation can be programmed in MATLAB. Note that Wang et al. [13,22] have verified the effectiveness of this co-simulation platform in investigating the ASD of LAV. Furthermore, they compared the virtual with actual ASD, measured by Abdo et al. [30], under the same scenario.

C. Experimental Design

Given the virtual simulations conducted in this study, there is a need for a scenario-based experimental design that can reflect various variables and handle well-designed scenarios [31]. In view of the advantages of the scenario-based design approach, a much-cited scenario design framework [28] was used, as shown in Fig. 3. In addition, this scenario-based design can explicitly and systematically present the information required for the generation of simulation scenarios [32].

![Fig. 3. Scenario design framework.](image)

Specically, the functional scenario has a high degree of abstraction, written or depicted in natural language, to clarify the scenario content, objective, and necessary components [28]. Based on the components defined in the functional scenario, the types and value ranges of their representative parameters are defined in the logical scenarios [28]. Finally, a concrete scenario is established by sampling the parameters and variables defined in the logical scenario [28].

1) Functional Scenario

Regarding this study, the functional scenario (see Fig. 4) can be expressed as a situation where the LAV drives along a particular road alignment. Still, as a fixed obstacle, TV is on the desired path ahead of the LAV.

![Fig. 4. Scenario design framework.](image)
Many previous findings have shown that a rear-end collision with another vehicle is the most common type of AV-involved crash [33]. Moreover, the vehicle is also the representative object (or obstacle) in the HV ASD analysis [5], where the object height for SD (0.6 m) refers to the vehicle’s taillight height. Therefore, TV was used in the scenario.

As shown in Fig. 4, the passenger vehicle for LAV and TV was selected according to the primary design vehicle in highway geometric design [5]. Also, the on-road passenger vehicle is one of the most critical manifestations of automated driving technology [1]. Therefore, the vertical alignment included crest, sag curves, and tangent grade. In addition, a one-lane road segment was selected to enable the LAV's driving path to overlap exactly the road centerline so as to explore the direct effect of geometry.

2) Logical Scenarios

To serve the functional scenario defined previously, we further defined the components, including vehicles (LAV and TV), road geometry, and LiDAR.

a) Vehicles

Component information of vehicles includes dimensions, motion states, and locations. The vehicle model of the Audi A8 provided by the simulation platform was adopted for both LAV and TV. The vehicle is 5.21 m long, 2.04 m wide, and 1.44 m high.

When measuring the ASD of HV, the ego vehicle is usually set to drive at a uniform speed, closely related to the road environment, especially the geometry [5]. Concerning the LAV, without external disturbances, its products (e.g., Tesla) drive at a uniform speed set by the driver’s desire [34]. To the authors’ best knowledge, personalized automated driving strategies [35] that can imitate speed characteristics of HV remain at the theoretical aspect.

Similar to the setting of speeds, to maximize the safety benefit, the LAV is primarily mandated to drive with a minimal deviation from the lane centerline [36]. This path feature is also consistent with that required in the ASD measurement. Therefore, a constant speed and a fixed driving path (i.e., lane centerline) were used for the LAV independent of geometric conditions.

Very few efforts were expended to measure AV's actual driving or operating speeds corresponding to various as-built geometric conditions, designed mainly by a vs-derived deterministic approach. In addition, to achieve better mobility, a speed closer to the safe margin supplied by the as-built road geometry could be the desired speed for AV. Therefore, vs corresponding to geometry was used as the driving speed of LAV.

Furthermore, the minimum speed within the AV’s ODD is usually larger than 40 km/h [37]. In addition, Varotto et al. [38] found an average speed of 107.2 km/h from the naturalistic driving data of AV, which were collected on high-type highways and normal driving conditions. Also, the driving risk is rarely attributable solely to the limited ASD when vs is larger than 100 km/h [39]. Therefore, we adopted the driving speed (i.e., vs herein) of LAV ranging from 40 km/h to 100 km/h with an interval of 20 km/h. As for the stationary TV, it can be positioned anywhere along the driving path of the LAV from the end of the road segment until it is detected.

b) Road Geometry

To investigate the effect of as-built highway geometry, all adopted values of vertical geometric elements comply with the Chinese design specification for highway alignment [40]. That could also exclude the other safety-failure modes regarding vehicle dynamics (e.g., rollover).

Tangent grades

As shown in Fig. 5, given a certain relative distance between the LAV and TV, adjusting the grade (iG) alone affects neither the relative location between vehicles nor between the TV and LiDAR FoV. Therefore, the ASD under different iG is supposed to be the same as that on the tangent. Since the specified maximum iG decreases with an increase in vs [40], iG of 4% corresponding to vs = 100 km/h was adopted.

![Fig. 5. Scenario design framework.](Image)

In addition, as mentioned above, the ASD for iG = 4% is the same as that on the tangent. Wang et al. [13] have simulated ASD of LAV on the tangent at NC = 64, ha = 1.44 m (refers to the roof of Audi A8), vs = 40-100 km/h, NR = 10 and 20. Their results show that the driving speed of LAV hardly affects the ASD on the tangent since there is neither lateral nor vertical relative movement between vehicles. Based on their results, average ASD over vs = 40-100 km/h at NR = 10 and 20 are 71 m and 43 m, respectively, which are much shorter than the minimum LTG (120 m at vs = 40 km/h) specified by [40]. Therefore, to reduce the unnecessary sample size, we adopted LTG ranging from 0 to 70 m and 0 to 40 m at NR = 10 and 20, respectively, with an interval of 10 m.

Vertical Curves

Regarding establishing vertical curve models in the simulation platform, the length (LV) and curvature (RV) of the vertical curve are related by \( LV = RV \times \omega \), where \( \omega \) is the algebraic difference in grades. A value of \( |\omega| \) of 4% was used, corresponding to iG. To satisfy the requirements of both LCV (or LSV) and RV (or RSV) specified by [40], their value ranges were selected or calculated based on the \( |\omega| \) of 4%, as listed in Table I. Note that the minimum values of their ranges should not be less than their limited minimum values (\( L_{lim,Vmin} \) and \( R_{lim,Vmin} \)).
specified by [40]; the maximum values are determined by reference to the common minimum values \((L_{\text{com}, \text{Vmin}} \text{ and } R_{\text{com}, \text{Vmin}})\) specified by [40]. The intervals of \(L_V\) and \(R_V\) are 10 m and 250 m, respectively. Specifically:

i) The minimum \(L_{CV}\) at \(V_D = 40 \text{ km/h}\) adopts the \(L_{\text{dim}, \text{Vmin}}\), and the minimum \(R_{CV}\) is calculated by \((L_{CV} / 4\%)\), while the minimum \(R_{SV}\) at \(V_D = 60\) to 100 km/h uses \(R_{\text{lim}, \text{Vmin}}\) and the minimum \(L_{CV}\) is calculated as \(4\% R_{CV}\).

ii) The minimum \(R_{SV}\) at \(V_D = 40\) and 60 km/h use \(R_{\text{lim}, \text{Vmin}}\), and the minimum \(L_{SV}\) is calculated as \(4\% R_{SV}\), while the minimum \(L_{SV}\) at \(V_D = 80\) and 100 km/h use \(L_{\text{lim}, \text{Vmin}}\), and the minimum \(R_{SV}\) are calculated as \(L_{SV} / 4\%\).

iii) The maximum \(L_V\) and \(R_V\) at \(V_D = 40\) to 80 km/h use those at \(V_D = 100 \text{ km/h}\) to capture as many ASD features along the vertical alignment as possible. Therefore, the minimum \(L_V\) and \(R_V\) selections at \(V_D = 100 \text{ km/h}\) also apply to its maximum \(L_V\) and \(R_V\).

| TABLE I |
| ADOPTED RANGES OF LENGTH AND CURVATURE OF VERTICAL CURVES. |
| --- | --- | --- | --- |
| Curve Type | Variable | Design Speed, \(V\) (km/h) |
| | \(L_{CV}\) (m) | 40 | 60 | 80 | 100 |
| Crest | [35, 400] | [56, 400] | [120, 260] | [40] |
| | \(L_{SV}\) (m) | [875, 10000] | [1400, 6500] | [3000, 10000] | [120, 210] |
| Sag | \(R_{CV}\) (m) | [35, 210] | [50, 210] | [80, 210] | [210] |
| | \(R_{SV}\) (m) | [875, 1250] | [1250, 2000] | [3000, 5250] | [5250, 5250] |

\(T:\) Tangent Grade and Vertical Curve

For the alignment of a tangent grade followed by a vertical curve, values or ranges of related geometric design elements (e.g., \(L_V\)) are consistent with those stated above. In addition, since the LAV always drives along the lane centerline and the LiDAR is mounted on the LAV’s centerline, the lane width and cross slope are not expected to affect the ASD. Therefore, a lane width of 3.75 m and a cross slope of 2% were adopted as per [40].

c) LiDAR

According to the comparisons of various commercially available LiDAR products [24,25,41-43], the most significant difference among them is \(N_C\) or vertical angular resolution \((= VFoV / (N_C – 1))\) if vertical channels are uniformly distributed. The frequently-used \(N_C\) values are 32, 64, and 128 for the multi-channel LiDAR, which has gradually become the requisite of high-level AV (e.g., Waymo).

On the contrary, many LiDAR manufacturers have reached a consensus on the design values of other technical parameters of their LiDAR products. Also, to eliminate the possible blind spot, they pay more attention to obtaining as good a horizontal-related sensing performance as possible, e.g., a wider horizontal FoV (HFoV).

According to the comparisons above, the adopted values of the LiDAR technical parameters are shown in Table II. Note that these values were selected concerning their general levels of current multi-channel LiDAR products instead of referring to a specific product. Also, to simplify the LiDAR model setting, the uniform and symmetrical distribution of vertical channels was selected, which enables the adopted \(N_C\) to correspond to vertical angular resolutions in order. For example, an \(N_C\) of 32 corresponds to a vertical angular resolution of 0.97 deg. In addition, since the investigated road segment only extends longitudinally, a HFoV of 120 deg is sufficient.

<p>| TABLE II |
| ADOPTED VALUES OF LiDAR TECHNICAL PARAMETERS. |</p>
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range</td>
<td>200 m</td>
</tr>
<tr>
<td>HFoV</td>
<td>120 deg = [-60, +60] deg</td>
</tr>
<tr>
<td>VFoV</td>
<td>30 deg = [-15, +15] deg</td>
</tr>
<tr>
<td>Horizontal angular resolution</td>
<td>0.40 deg</td>
</tr>
<tr>
<td>Vertical angular resolution</td>
<td>0.97 deg, 0.48 deg, 0.24 deg</td>
</tr>
<tr>
<td>(N_C)</td>
<td>32, 64, 128</td>
</tr>
<tr>
<td>Frame rate</td>
<td>20 Hz</td>
</tr>
</tbody>
</table>

Only one high-type LiDAR model with technical parameters listed in Table II was established because it is the typical LiDAR configuration for detecting long-distance targets [44]. Furthermore, two widely-used mounting locations were considered: front-end centers of LAV’s roof and bumper (or headlights) [10]. Therefore, the adopted \(h_{\text{real}}\) are 1.44 m and 0.60 m, corresponding to the heights of Audi A8’s roof and headlights, respectively.

As stated in Section 1, receiving sufficient laser points reflected from the target is essential for LiDAR-based detection algorithms. Although different algorithms might require more or fewer laser points, a general-level \(N_T\) could be determined by referring to previous studies. Specifically, Teichman et al. [45] found that the accuracy of the proposed algorithm decreases to approximately 80% as fewer than 50 laser points are received. The accuracy of the algorithm proposed by Suganuma et al. [46] drops to 85% when the number of points reduces to 25. Furthermore, Abdo et al. [30] and Wang et al. [13,22] have investigated the effective range of LiDAR at many \(N_T\) values, e.g., 10, 20, etc. Therefore, to reduce the sample size, two typical values of \(N_T\) with two-fold relation: 10 and 20 were adopted.

3) Concrete Scenarios

Using the pairs sampling approach [32], the experimental values were selected by considering all possible combinations within the set range according to the user-defined categories. Due to the different geometry properties of vertical curves and tangent grades, two categories i) vertical curves and ii) tangent grade and vertical curve, were considered for the concrete scenarios.

Fig. 6 shows the parameters-variables pairs sampling for concrete scenarios. As noted, to reduce the sample size, i) in the category of vertical curves, \(h_{\text{real}} = 0.6 \text{ m}\) is only paired with \(N_C = 64\); and ii) in the category of tangent grades and vertical curves, only \(N_C = 64\) and \(h_{\text{real}} = 1.44 \text{ m}\) are selected in ranges of \(N_C\) and \(h_{\text{real}}\), respectively. Furthermore, the parameters and variables of each component are paired (see ‘+’ in Fig. 6) and variables between each component are paired (see solid or dashed straight arrows in Fig. 6).
Fig. 6. Parameters-variables pairs sampling for the concrete scenarios.

D. Experimental Process

Fig. 7 shows the entire experimental process for each trial. As noted, first, according to the scenario design, two categories of concrete scenarios are established in the simulation platform. After starting the simulation, the ASD in specific geometric and LiDAR conditions is estimated by collecting \( N_i \), comparing it with \( N_T \), and outputting \( L_i \). Finally, the ASD profiles for all concrete scenarios are created. More details regarding the programming of ASD estimation were described in previous studies \([13,22]\).

Fig. 7. Experimental process.

IV. RESULTS AND DISCUSSION

A. How Far Can LAV See?

1) Vertical Curves

According to the results in ASD profiles, Fig. 8 shows ASD at \( N_C = 64 \) and \( h_{ml} = 1.44 \) m along vertical curves with different \( R_V \) (\( = 4\% R_V \)). As noted, ASD increases linearly as \( R_V \) increases, then fluctuates around a general level. Specifically, the fluctuation amplitudes are about 20 m and 10 m at \( N_T = 10 \) and 20, respectively. Compared with the ASD results simulated by Wang et al. \([13,22]\), these fluctuations along vertical curves with different \( R_V \) are much larger than those along the horizontal curves with different radii (about 5 m and 2 m at \( N_T = 10 \) and 20, respectively), but the former frequency is lower. Also, there are considerable overlaps between ASD curves at different \( V_d \), which means that \( V_d \) has little effect on the ASD along vertical curves.

Fig. 8. ASD at \( N_C = 64 \) and \( h_{ml} = 1.44 \) m: (a) Crest curves, (b) Sag curves.

The ASD, limited by the \( |\delta| \) of 4\%, can cover the entire \( L_V \) (\( = 4\% R_V \)) at a small \( R_V \), but its actual features appear as \( R_V \) increases to a critical \( R_V \) (\( R_{V\text{crit}} \)), i.e., ASD \( \approx L_V \) if \( R_V \leq R_{V\text{crit}} \). The features mentioned above are attributed to the following factors:

i) Prerequisite: instead of the horizontal angular resolution, the vertical angular resolution plays a significant role in determining the ASD along the vertical curves because there is no lateral movement between vehicles;

ii) A larger fluctuation amplitude: the vertical angular resolution is larger than the horizontal angular resolution at \( N_C = 64 \), and some of the laser points are emitted into the air or blocked by the pavement;

iii) A lower frequency and insignificant effect of \( V_d \): the pitch angle (or vertical displacement) between vehicles on the vertical curves is smaller than the yaw angle (or lateral displacement) on horizontal curves.

Moreover, as shown in Figs. 8(a) and 6(b), the ASD at \( N_T = 10 \) is longer than at \( N_T = 20 \), and the ASD on the crest curve is the same as on the sag curve. Specifically, ASD \( \approx 55-75 \) m and 40-50 m at \( N_T = 10 \) and 20, respectively. This means that the as-built crest-curve pavement profile does not have a disadvantage in ASD (i.e., blocking the laser beams) compared with the sag-curve pavement.

Since the insignificant effect of \( V_d \) on ASD, the ASD at \( V_d = 40 \) km/h was shown in Fig. 9 to explore the effects of \( N_C \) and \( h_{ml} \) further. As shown in Figs. 9(a) and (b), ASD increases with \( N_C \). Notably, more \( N_C \) or less \( N_T \) can reduce the difficulty of TV detection, thus increasing ASD, which is consistent with the previous finding \([13,22]\).
Figs. 9(c) and (d) show that the ASD curve at \( h_{\text{ml}} = 0.60 \) m is mostly above that at \( h_{\text{ml}} = 1.44 \) m, especially when \( RV_C \) or \( RV_S \) is large. Due to the limited \( \omega \) and large \( RV \) similar to the horizontal alignment, the closer the \( h_{\text{ml}} \) (0.60 m) is to the middle height of TV (1.44 / 2 = 0.72 m), the more the laser points can be emitted to it by the LiDAR with uniformly and symmetrically distributed vertical channels, as illustrated in Fig. 10. This also aligns with the finding on horizontal curves [22]. However, this would contradict the opinion that a higher \( h_{\text{ml}} \) does enable a LiDAR to receive more target information without occlusion. To justify that opinion, it needs to assume that the TV can be detected once its boundary enters LiDAR’s FoV or it is applied in urban streets with several vehicles between LAV and TV. To trade off the pros and cons of a higher or lower \( h_{\text{ml}} \), some LiDAR products (e.g., Velodyne’s Alpha Prime) mounted on the vehicle roof use a VFOV with a downward offset and a more concentrated resolution distribution towards the road pavement, as depicted in Fig. 10.

To compare the ASD on sag curves with that on crest curves from the average perspective and to capture the \( RV_{\text{cri}} \), Table III shows the \( RV_{\text{cri}} \) and the average ASD (\( \overline{\text{ASD}} \)) when \( RV > RV_{\text{cri}} \). Note that due to the adopted \( RV \) interval of 250 m, the resulting \( RV_{\text{cri}} \) might differ from the actual value.

**TABLE III**

<table>
<thead>
<tr>
<th>( NC )</th>
<th>( h_{\text{ml}} ) (m)</th>
<th>( NV )</th>
<th>( RV_{\text{cri}} ) (m)</th>
<th>( \overline{\text{ASD}} ) (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>1.44</td>
<td>10</td>
<td>1375</td>
<td>51.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>875</td>
<td>34.4</td>
</tr>
<tr>
<td>64</td>
<td>0.60</td>
<td>10</td>
<td>1625</td>
<td>70.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>1125</td>
<td>47.6</td>
</tr>
<tr>
<td>1.44</td>
<td>10</td>
<td>1875</td>
<td>61.9</td>
<td>66.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>1125</td>
<td>45.2</td>
</tr>
<tr>
<td>128</td>
<td>1.44</td>
<td>10</td>
<td>2250</td>
<td>89.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>1625</td>
<td>89.9</td>
</tr>
</tbody>
</table>

As shown in Table III, except at \( NC = 64 \) and \( h_{\text{ml}} = 0.60 \) m the \( RV_{\text{cri}} \) for crest curves is smaller than for sag curves, the former is larger than the latter in other conditions. Also, except at \( NC = 64 \) and \( h_{\text{ml}} = 1.44 \) m the \( \overline{\text{ASD}} \) on sag curves is longer than on crest curves. They are basically the same in other conditions. These indicate that a lower \( h_{\text{ml}} \) does cause a shorter ASD of crest curves when \( RV_C < RV_{\text{cri}} \); a higher \( h_{\text{ml}} \) enables the ASD to cover a wider range of \( LV_C \), but the ASD substantially decreases when \( RV_C > RV_{\text{cri}} \), which could be explained by Fig. 11.

![Fig. 11. Scenario comparison of the crest and sag curves under different \( h_{\text{ml}} \) and the same \( RV \).](image)

As shown in Fig. 11, given the same \( RV \), the FoV above the pavement of the crest curve is larger than that of the sag curve, according to the geometric relation. However, on the crest curve, the laser pulses from the lower LiDAR channels would be easily blocked, and most upper beams point to the air. On the contrary, most upper laser beams shoot to the TV on the sag curve. Therefore, as \( RV \) increases, both vertical curves approach the tangent section.

It should be noted that the current \( \omega \)-derived design of the crest curve cannot wholly block the FoV of LAV due to the limited \( \omega \), which is required by vehicle dynamics safety [40]. As shown in Fig. 11, although the area of FoV above the pavement reduces as \( h_{\text{ml}} \) lowers from 1.44 m to 0.60 m, FoV can still cover the TV in the same position ahead. Also, the actual ASD on vertical curves (see \( \overline{\text{ASD}} \) in Table III) is significantly shorter than the range of LiDAR (200 m).

Moreover, given the same \( NC \), \( NV \), and \( h_{\text{ml}} \) conditions, \( \overline{\text{ASD}} \) on vertical curves (see Table III) is the same as that on tangent sections [13], but it is shorter than that on the horizontal curves [13,22], especially for \( NC = 128 \) and \( NV = 10 \) (shorter by about 10 m). That further demonstrates the little effect of vertical curve pavement on ASD.

Additionally, it is noteworthy that the LAV’s FoV might be obstructed by overhead structure (e.g., flyover) on sag curves,
as illustrated in Fig. 12. Therefore, whether such a structure reduces the ASD on sag curves is further examined.

**Fig. 12. Scenario at undercrossings.**

Since that as-built structure shall be designed to provide sufficient vertical clearance ($h_{VC}$) for the HV’s RSD, it is convenient to calculate the ASD and then compare it with the ASD of LAV. The ASD of LAV would be limited to ASD_{under} if ASD_{under} ≤ ASD. Otherwise, the structure would not obstruct the LAV’s FoV. The ASD is given by [40] as follows.

$$\text{ASD}_{\text{under}} = \sqrt{\frac{\left( h_{VC} - h_{E} \right)^2 + \left( h_{VC} - h_{O} \right)^2}{R_{VS}}}.$$  \hspace{1cm} (1)

where ASD_{under} is the ASD at the undercrossing, and $h_{E}$ and $h_{O}$ are the heights of the human driver’s eye and object, respectively. The empirical values of $h_{VC}, h_{E},$ and $h_{O}$ are 4.5 m, 1.5 m, and 0.75 m, respectively [40].

Given the same $R_{VS}$ listed in Table 1, ASD_{under} calculated by (1) is significantly longer than ASD of LAV. Accordingly, ASD would not be affected by as-built structures on sag curves.

2) **Tangent Grade and Vertical Curve**

Based on the relationship between ASD and $R_{V}$ stated above, only four typical $R_{V}$, i.e., both minimum and maximum values of $R_{V}$ ranges at $V_d = 40$ km/h (see Table 1), were adopted to investigate the independent effect of $L_{TG}$. Figs. 13(a) and (b) depict the ASD at $N_C = 64$ and $h_{nal} = 1.44$ m along the tangent grade and vertical curve with different $L_{TG}$.

**Fig. 13. ASD on: (a) Tangent grade and crest curve, (b) Tangent grade and sag curves.**

As shown in Figs. 13(a) and (b), ASD still fluctuates with $L_{TG}$. In general, with an increase in $L_{TG}$, i) when $R_{V}$ adopts the maximum value, ASD increases and decreases at $N_{T} = 10$ and 20, respectively; and ii) when $R_{V}$ adopts the minimum value, ASD still increases linearly (ASD = $L_{TG} + L_{V}$) and then rises gradually ($ASD < L_{TG} + L_{V}$).

Regarding the road segment covered by LiDAR FoV, the overall curvature of its longitudinal profile decreases as the proportion of a tangent grade increases. Accordingly, the relative path distance within the FoV decreases based on the geometric relation, as with the ASD at larger $R_{V}$ and $N_{T}$. Given that a large $R_{V}$ causes the longitudinal road profile to approach horizontal alignment, this aligns with the previous finding that the higher the $N_{T}$, the more consistent the change of ASD with that relative path length [13,22]. On the contrary, a lower $N_{T}$ allows a longer ASD, but that ASD would fluctuate instead of complying with the change of that relative path length due to sparser channels. Furthermore, ASD results at the minimum $R_{V}$ are consistent with those in Figs. 8(a) and (b) because the additional tangent grade length can be considered the increasing $R_{V}$.

**Table IV further lists $\overline{ASD}$ when $ASD < L_{TG} + L_{V}$.** As shown in Table IV, all $\overline{ASD}$ results are basically the same as those corresponding results at $N_{C} = 64$ and $h_{nal} = 1.44$ m on complete vertical curves (see Table III), except that $\overline{ASD}$ (= 68.1 and 68.7 m) at $N_{T} = 10$ on the tangent grade and crest are much larger than 61.9 m. It is necessary to highlight such a $\overline{ASD}$ reduction from a tangent grade followed by a crest curve to a complete crest curve at those LiDAR-related features.

<table>
<thead>
<tr>
<th>Alignment combination</th>
<th>$R_{V}$ (m)</th>
<th>$N_{T}$</th>
<th>$\overline{ASD}$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tangent grade and crest curve</td>
<td>875</td>
<td>10</td>
<td>68.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>44.9</td>
</tr>
<tr>
<td></td>
<td>10000</td>
<td>10</td>
<td>68.7</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>46.6</td>
</tr>
<tr>
<td></td>
<td>875</td>
<td>20</td>
<td>66.4</td>
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<tr>
<td></td>
<td></td>
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<td>46.1</td>
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<tr>
<td></td>
<td>5250</td>
<td>10</td>
<td>67.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20</td>
<td>45.7</td>
</tr>
</tbody>
</table>

Finally, both ASD (see Figs. 9 and 13) and $\overline{ASD}$ (see Tables III and IV) results could answer ‘how far can LAV see?’.

B. **How Fast Shall LAV Drive?**

According to [1], AV automation levels that are still constricted by ODD include L3 and L4. As proposed by Wang et al. [10], RSDs of L3 and L4 (RSD_{L3} and RSD_{L4}, respectively) are calculated via (2) and (3), respectively.

$$RSD_{L3} = 0.278 \times V_d \times t_{p,L3} + \left[ \frac{V_d}{\frac{A_{dp}}{9.81}} \pm i_{g} \right] \times t_{T} - 254 \left( \frac{A_{dp}}{9.81} \pm i_{g} \right) \cdot t_{T}^2.$$  \hspace{1cm} (2)
\[
RSD_{L4} = 0.278 \times V_d^2 \times t_p_{L4} + \frac{V_d^2}{254 \times \left( \frac{A_d}{9.81} \right) \pm i_0}. \tag{3}
\]

where \(t_p_{L3}\) and \(t_p_{L4}\) are perception-brake reaction time of L3 and L4, respectively. \(t_r\) is the driver’s takeover time from the L3 automation system, \(A_d\) is the deceleration rate activated by the L3 automation system during \(t_r\). \(A_G\) is a preset deceleration rate activated by the L3 automation system during \(t_r\), \(A_{dp}\) and \(A_d\) are 4.3 s, 0.5 s, 3.8 s, 2.5 m/s², and 3.4 m/s², respectively, which were adopted by Wang et al. [10]. Since the adopted \(i_c\) of ±4% and maximum \(|i_c|\) of 4%, the minimum and maximum \(i_c\) are 0 and 4%, respectively, for sag curves.

As \(V_d\) has little influence on ASD, \(V_{\text{max}}\) for LAV under a given \(V_r\) could be calculated by setting ASD (see (1)) equal to RSD (see (2) or (3)). Figs. 14(a)-(d) show \(V_{\text{max}}\) for L3 and L4 on vertical curves. Note that only the ASD is considered at \(V_r\).

As shown in Figs. 14(a)-(d), \(V_{\text{max}}\) for L4 is much larger than that for L3 due to RSD_{L3} > RSD_{L4} given the same \(V_d\) and geometry conditions. That is in line with the case of horizontal alignment [10]. Also, \(V_{\text{max}}\) on upgrades is larger than on downgrades, and their difference increases with more \(N_c\). Other \(V_{\text{max}}\) features related to \(V_r\), \(N_c\), \(N_t\), and \(h_{\text{ind}}\) are consistent with the case of ASD features.

Additionally, since the market maturity of AV cannot be achieved overnight [48], their driving speed on as-built highways needs to be comparable to that of HV or vehicles with lower automation levels. The \(V_d\) of a specific highway section can be tentatively regarded as such a general driving speed of most vehicles. Therefore, to ensure speed consistency with \(V_d\) (40-100 km/h), a typical \(V_{\text{max}}\) range of \((V_d - 20 \text{ km/h})-V_d\) [49,50] (Hamzie et al., 2017; Chen et al., 2022) corresponding to the specified \(V_r\) range was adopted (see Figs. 14(a)-(d)). Given specific geometry, LiDAR, and automation level conditions, if \(V_{\text{max}} > V_d\) and \((V_d - 20 \text{ km/h}) < V_{\text{max}} < V_d\), such an LAV driving with \(V_d\) and \(V_{\text{max}}\), respectively, could satisfy both SD and speed consistency requirements. However, if \(V_{\text{max}} < (V_d - 20 \text{ km/h})\), the speed consistency of LAV driving with \(V_{\text{max}}\) will fail. As shown in Figs. 14(a)-(d), generally, \(V_{\text{max}}\) for L3 and L4 at \(N_t = 10\) range from 30-55 km/h and 55-85 km/h, respectively, but both \(V_{\text{max}}\) for L3 and L4 reduce by 10-15 km/h at \(N_t = 20\).

Such a fluctuating \(V_{\text{max}}\) along the alignment specified by a certain \(V_d\) could be feasible in an individual AV’s dynamic control, which improves the vehicle-based ODD. However, \(V_{\text{max}}\) might not be attractive to road administrators due to its lack of generality. To obtain a more general \(V_{\text{max}}\) for the speed limit, the average maximum speed (\(V_{\text{max}, \text{avg}}\)) within the specified \(V_r\) range was further calculated, as shown in Table V. Note that \(V_{\text{max}, \text{avg}}\) was separately calculated using the maximum speed of the upgrade (\(V_{\text{max}, \text{u}}\)) and downgrade (\(V_{\text{max}, \text{d}}\)).

### Table V

<table>
<thead>
<tr>
<th>(N_c)</th>
<th>(h_{\text{ind}}) (m)</th>
<th>(N_t)</th>
<th>Driving Automation level</th>
<th>Crest curves (V_d) (km/h) and specified (R_{\text{max}}) (m range)</th>
<th>Sag curves (V_d) (km/h) and specified (R_{\text{max}}) (m range)</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>1.44</td>
<td>10</td>
<td>L3</td>
<td>[34, 35]</td>
<td>[40, 10000</td>
</tr>
<tr>
<td>20</td>
<td>1.44</td>
<td>10</td>
<td>L4</td>
<td>[25, 26]</td>
<td>[40, 10000</td>
</tr>
<tr>
<td>64</td>
<td>0.60</td>
<td>10</td>
<td>L3</td>
<td>[62, 65]</td>
<td>[40, 10000</td>
</tr>
<tr>
<td>64</td>
<td>0.60</td>
<td>20</td>
<td>L4</td>
<td>[49, 52]</td>
<td>[40, 10000</td>
</tr>
<tr>
<td>1.44</td>
<td>1.44</td>
<td>10</td>
<td>L3</td>
<td>[32, 33]</td>
<td>[40, 10000</td>
</tr>
</tbody>
</table>
As shown in Table V, $\bar{V}_{\text{max}}$ with an exact value (see yellow or light red/green cells) can be used as a speed limit for vertical curves. Additionally, the $V_{\text{max}}$ on the tangent grade and vertical curve are basically the same as those on vertical curves due to the same ASD except the case at $N_C = 64$, $h_{\text{ml}} = 1.44$, and $N_T = 10$ on the tangent grade and crest curve. In that case with ASD $\approx 68$ m, $V_{\text{max}}$ would increase by about 4 km/h. However, more attention to a smaller $V_{\text{max}}$ should be paid on subsequent crest curves. Finally, the results of both $V_{\text{max}}$ (Fig. 14) and $V_{\text{max}}$ (Table V) could answer the question, 'how fast shall LAV drive?'.

Our answers to these two questions appear to fall well short of what the general public expects for AV’s potential advantages, i.e., it can see farther and drive faster. This is mainly attributed to the specific experimental designs related to LiDAR adopting only a single multi-channel LiDAR and $N_T$ of more than one laser point, which have been justified above. Therefore, how LAV safely adapts to the as-built vertical alignment could be solved by referring to the proposed speed limits. Otherwise, to help the LAV see farther and drive faster on as-built vertical alignment, it is suggested to equip more LiDARs, incorporate more channels, or develop algorithms reducing $N_T$. In addition, we conjecture that the detection capability beyond SD can be achieved by deploying roadside monitoring sensors [51], which is also beneficial to improve LAV’s $V_{\text{max}}$.

V. CONCLUDING REMARKS

This study adopts a virtual simulation method and conducts a scenario-based experimental design to answer the question, 'how far can LAV see on highway vertical alignments?'. Then, SD and speed consistency requirements are considered to answer the question, 'how fast shall it drive?' To the authors' best knowledge, this study is the first attempt that reconsiders LAV’s ASD issues on vertical alignments and proposes the corresponding speed limits. Based on the study, the following comments are offered:

- ‘How far can LAV see on highway vertical alignments?’ depends on variables regarding vertical geometric elements and LiDAR. Specifically, ASD increases as $N_T$ decreases, $N_C$ increases, or $h_{\text{ml}}$ decreases. Importantly, ASD on crest curves is the same as on sag curves or tangent sections, which means that the as-built crest-curve pavement profile would not limit ASD. Also, since LiDAR’s vertical angular resolution is generally coarser than the horizontal, ASD fluctuates around ASD as $R_V$ increases, which is more noticeable than horizontal curves.

Consequently, these results provide new insight into effects attributable to features of vertical geometry and LiDAR on LAV’s ASD variations. They further highlight the limited perception capability of current AV from the perspective of road safety.

- ‘How fast shall it drive?’ further depends on LAV’s automation level besides those variables. Specifically, $V_{\text{max}}$ for L3 and L4 range from 30-55 km/h and 55-85 km/h, respectively, at $N_T = 10$; range from 20-40 km/h and 45-75 km/h, respectively, at $N_T = 20$. An important practical implication of this study is related to the proposed speed limits within the road section, which could regulate L3 and L4 safe speeds and improve road-oriented ODD specifications. Also, the results of $V_{\text{max}}$ and speed limits demonstrate that only at $N_C = 128$ and $N_T = 10$ would L4 be compatible with as-built vertical alignment with $V_d = 100$ km/h. However, even under these conditions, L3 can only adapt to the vertical profile with $V_d = 60$ km/h.

- The main limitation of this study is a lack of consideration of weather effects. On the one hand, adverse weather (e.g., rainy days) would impair LiDAR functions and thus shorten ASD [30]. However, on the other hand, the weather might also impact RSD due to the wet pavement or longer takeover time. Additionally, this study only considers one AV type of passenger vehicle. However, besides ASD, speed limits for heavy-duty AV on vertical alignment shall pay attention to their braking capacity and truck drivers’ reaction times [10]. Therefore, extensive tests, including weather effects and automated trucks, should be conducted in the future. Also, in the future, we are interested in extending road geometry from two-dimensional to three-dimensional, i.e., combined alignment, which would be more consistent regarding the reality of geometry conditions.

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