Short Term Future Proofing Strategies for Local Agencies to Prepare for Connected and Automated Vehicles

Shauna Hallmark[1], Jonathan Wood[2], David Veneziano[3], and Theresa Litteral[4]

Institute for Transportation, Iowa State University, Ames, Iowa, shallmar@iastate.edu
Institute for Transportation, Iowa State University, Ames, Iowa, jwood2@iastate.edu
Institute for Transportation, Iowa State University, Ames, Iowa, dvenez@iastate.edu
Institute for Transportation, Iowa State University, Ames, Iowa, litteral@iastate.edu

Abstract

Connected and automated vehicle technologies hold the potential to produce a number of safety, mobility, and environmental benefits. The benefits of connected vehicle technologies are expected to be wide ranging and include reduced crashes, improved mobility, and reduced emissions. However, transitioning highway infrastructure to be ready for connected and automated vehicles will ultimately require a significant investment in infrastructure upgrades, new technologies, power, and connectivity. Agencies are already grappling with how and where to invest scarce resources to meet existing needs and addressing current and future CAV needs add an additional burden. This is particularly true for local transportation agencies who already face worker shortages and resource shortfalls. As a result, there is a need for local transportation agencies to 1) understand what the potential benefits of connected vehicle technologies are, and 2) how they should be preparing for the transition to such technologies for the infrastructure and fleets that they manage.

This paper summarizes results of a research project which evaluated infrastructure elements needed for CAV deployment which may be under the purview of local transportation agencies and summarizes what is known about the direction of CAV needs, such as pavement markings.

Since local agencies are resource constrained, this research provided information so that local agencies can leverage ongoing activities and resources to prepare for CAVs. For instance, when restriping, an agency could invest additional resources to ensure pavement markings are compatible with upcoming standards for autonomous vehicles.

Keywords: connected/autonomous vehicles, local agency, pavement markings, future proofing

1. Introduction

Connected and automated vehicle (CAV) technologies, along with advanced driver assistance systems (ADAS), hereafter simply referred to as CAV, hold the potential to result in a number of safety, mobility, and environmental benefits for the users and operators of the surface transportation systems. The benefits of CAV technologies are expected to be wide ranging and include reduced crash rates and severity, improved mobility, and reduced emissions (1, 2, 3, 4, 5). CAVs have different functional requirements compared to non-CAVs. Connected vehicles obtain information primarily through information sent via signals from other vehicles (V2V) or from the infrastructure (V2I) which requires infrastructure elements such as roadside units (RSU). Automated vehicles and Advanced Driver Assistance Systems (ADAS) use cameras and other sensors (e.g., radar, lidar, and sonar) to read and interpret the roadway and roadside environment. Data from the various sources (sensors on the vehicle and connected-vehicle communications) are then processed by computers on the vehicle and used to provide feedback to the driver or to initiate vehicle-controlled maneuvers (dependent on the capabilities of the individual vehicles). Consistency in signage, markings and design (along with consistency in retroreflectivity and other factors) are less likely to result in conditions that these systems will struggle to interpret and successfully navigate. For instance, it has been shown that sign design consistency is an area where lack of consistency leads to difficulties for artificial intelligence (AI) in accurately and consistently identifying and interpreting both sign class and meaning (6).

Local transportation agencies, such as counties and cities, which manage a significant portion of the roadway network in the United States (US), are expected to be impacted by the transition to CAV technologies. These agencies can also expect to benefit from CAV technologies through aspects such as a reduced need to construct roadway infrastructure (fostered by mobility improvements), increased fleet safety (e.g., maintenance vehicles in plowing operations), and other benefits. However, transitioning highway infrastructure to be ready for CAVs could ultimately require a significant investment in infrastructure upgrades, new technologies, and power and connectivity. It will also change how agencies should prioritize resources for optimizing allocation and maximizing benefits. Compounding this transition is that both human and autonomous vehicles may share the roadway space for some time.

Agency staff are already grappling with how and where to invest scarce resources to meet existing needs. As a result, there is a need for local agencies to not only understand what the potential benefits of CAV technologies are, but also how they can be preparing for and potentially leveraging the transition to such technologies for the infrastructure and fleets that they manage.

This report summarizes current information and research on the infrastructure and technologies that local agencies should be aware of to prepare for CAVs and to support research, development, and implementation efforts on their systems in the short term.

2. Technological Performance of CAV

An understanding of how CAV uses transportation infrastructure assets to gain information is necessary for agencies to understand how to best prioritize implementation and maintenance of those assets to meet the needs of both human drivers and CAV. Current CAV systems use an array of sensors, computing resources, and artificial intelligence (AI) to self-navigate. Sensors include cameras, radar, LiDAR, GPS, ultrasonic sensors, etc., each of which has its own strengths and limitations. Cameras collect visual data (images, video) which are interpreted by image processing software and machine learning. Tesla, for instance, has 8 external facing cameras. Other vehicles rely on a variety of sensors, with differing number of each sensor type depending on the vehicle used. For instance, Waymo and ArgoAI use a combination of cameras (Waymo uses 19 cameras on the Chrysler Pacifica and 29 cameras on the Jaguar I-PACEs), radar, and LiDAR to measure the surrounding environment and GPS for location.

Cameras
Cameras provide high resolution and detail but are less ideal for calculating depth perception and struggle in adverse weather and in certain lighting conditions (e.g., low-light and camera blinding from bright lights and the sun). Cameras can also have issues due to lack of contrast in some conditions (7).

Camera systems rely on light bouncing off surroundings and then being captured by a charged couple device (CCD) or complementary Metal Oxide Semiconductor (CMOS) which can be designed to be highly sensitive to the amount of light available enabling systems to operate in low light situations (dawn, dusk, inclement weather). Sensors may be complemented by thermal imaging or forward-looking infrared cameras which can detect heat radiated from an object to assist in detection and positioning the object detected. These cameras have varying ranges for being able to identify objects. For instance, Tesla Autopilot uses cameras that have a max range of 250 meters (8).

LiDAR
LiDAR uses light pulses which are reflected off surfaces to create a 3-D map of the surrounding area and provides accurate depth perception but has limitations in adverse weather conditions (9). LiDAR is also useful for object detection and tracking, although a recent article noted that, due to the physical limitations of LiDAR, only vehicles can effectively be detected and that the best systems tested had an average precision of 52.4% in detecting pedestrians (10). LiDAR technologies are being developed to overcome conditions that limit the usefulness of traditional automotive LiDAR (such as fog, smoke, rain, and snow), but these technologies are not ready for field implementation (11). One of the key limitations to LiDAR technologies is range. One of the longest ranges in the automotive LiDAR sensors currently in production has a maximum range of 400 meters (12).

Radar
Radar is used in many CAV applications (e.g., automatic emergency braking, adaptive cruise control, etc.). The Hyundai Ionic sensor array for its ADAS features includes a front LiDAR with a 130-degree array, front, mid- and long-range radar, side radars with 110-degree array, rear radars with 150-degree array, and a 3-camera system (13). Most adaptive cruise control systems also use radar. Radar uses radio wave-based sensors to detect and track presence, direction, and speed of surroundings objects but is not able to detect and track direction and speed of objects. Radar does not have many of the weather-based limitations that cameras and LiDAR have but can struggle in areas with significant amounts of metal or when there is a significant amount of radar units in the area (i.e., radar congestion) which can lead to false alarms and processor confusion (14, 15). Some of the long-range radars in production can identify objects as far as 300 meters away (16).

GPS and Other Sensors
A global positioning system (GPS) is often used for position and direction. GPS is a well-established technology and has well-known limitations. The accuracy of the GPS coordinates is dependent on multiple factors including the type of system (e.g., Global Navigation Satellite Systems, or GNSS, which is often used in automotive GPS), number and locations of satellites (including clustering and location relative to the horizon), atmospheric refraction and other atmospheric-related errors, multipath errors, satellite drift, lost signals, etc. Thus, GPS is typically only used for general positioning and directions while the local navigation is based on the cameras, radar, and LiDAR sensors.

Other sensors may include microphones which can pick up audio signals such as emergency sirens (17). It can also include ultrasonic sensors which are effective for short-range sensing at low speeds. These sensors are used for specific tasks and are typically not the main sources of data used in CAV systems.

Sensor Data Processing and Decision Making
Computer systems process and organize the data from the sensors into actionable information for the driver or the automated vehicle control systems. Image recognition software identifies objects in images and is used in machine-based tasks such as labeling image content with meta-tags, searching image content, and image recognition which uses deep learning (9). Neural networks identify patterns in the data, and which is fed to machine learning algorithms. Machine learning algorithms allow an automated vehicle to work in common situations and learn and adapt from uncommon situations. Deep learning algorithms allow the vehicle to incorporate more information, enabling it to make more nuanced driving choices (9). Due to the limitations of each of the sensor types, these processes typically rely on multiple sensors providing consistent results to prevent incorrect conclusions and actions (i.e., redundancies).

Two primary issues that impact the ability of these systems to accurately assess the operating environment in real-time are unpredictability and complexity. Unpredictability may cause the system to misinterpret actions and react inappropriately. For instance, varying levels of wear for assets such as pavement markings, lack of consistency, or poor contrast in pavement markings make them difficult to interpret. Complexity includes environments which cause visible occlusion or optical illusions due to phenomena such as weather, reflections from surfaces, etc. This also includes signs or other infrastructure placed at angles or positions where they are more difficult to interpret. FHWA conducted a request for information to better understand infrastructure needs for CAV. One of the top themes was greater uniformity, quality, and consistency in road marking and traffic control devices (18).

3. Pavement Markings

Longitudinal pavement markings provide two functions for CAVs. First, they indicate the forward road alignment. Second, they are used to locate the vehicle within the cross section of the road. As a result, pavement markings are particularly important for CAVs (19, 20). The Federal Highway Administration (FHWA) (US) has stated that automakers have indicated that pavement markings are the most significant infrastructure characteristic needed for CAVs (21).

Pavement markings are identified through image processing. A camera sends digital images to the image signal processor (ISP) and the information is decoded using pixel detection. Although each OEM have their own proprietary algorithms, the basic premise of pixel detection remains the same. Each image is made up of pixels which are assigned a value based on intensity (light versus dark). Machine vision algorithms look for differences between pavement marking pixels and road pixels. The simple algorithms calculate and look for large differences between adjacent pixels; more complicated algorithms calculate the rate of change and creates a linear slope with a steep slope which is used to find edges, another algorithm uses similar calculations as the edge detection method but considers changes in two directions, and a final method uses deep learning to train the system to detect and classify objects. Each of the methods use “thresholding” which looks for values which meet a minimum threshold. As a result, sufficient contrast is the key criteria for identification of pavement markings (22).

Davies (23) evaluated retro reflectivity, contrast ratio, and width of pavement markings to assess how these have an impact on machine-vison performance. Retroreflectivity was found to be the most important factor for nighttime performance, but during the daytime, retroreflectivity had little impact on performance. The luminance contrast ratio was the most important factor for daytime machine-vision performance. Burghardt et al (23) evaluated eight types of pavement markings in a wind tunnel to assess recognition by typical machine vision (MV) equipment. Visibility by both cameras and LiDAR was important. They noted that in the case of cameras, a contrast ratio (CR) above 2.0 is deemed sufficient for pavement marking recognition but found no simple threshold for LiDAR since recognition depends on the algorithms utilized, number of detected points, and other information. They also indicated poor recognition of pavement markings in rainy conditions is challenging for both human and MV due to light scattering and reflection by water particles which increases noise. One suggested remedy was use of glass beads with higher RI. They noted key parameters for pavement marking recognition by both human drivers and MV is visibility and retroreflectivity. Carlson (24) summarized available recommendations and noted a threshold ratio of luminance (CIE Y) provided adequate machine vision detection (US studies) while the European Union Road Federation has recommended minimum maintained contrast levels of 3:1 with a preferred level of 4:1.

Since contrast and visibility are key, many agencies are using contrast markings. 3M conducted a pilot program in conjunction with the Michigan DOT (MDOT) to design new pavement markings, signing, and other connected vehicle infrastructure to facilitate AVs (26). They reported that contrast is key to positioning and have developed a product that is white in the middle with black edging, along with wet reflectivity, to assist with visibility during rain events (26, 27).

Many agencies use curbs to delineate the right-hand edge of a travel lane. However, the lack of contrast may make it difficult for machine visioning systems to interpret this feature. As a result, Carlson (24) also noted lane lines may be advantageous when curbs are present.

Figure 1: Overlapping Pavement Markings (Image source: Shutterstock)

Discontinuities in pavement markings also make it difficult for the sensors to predict where the vehicle is in the lane, causing the vehicle to rely on other features such as the edge of roadway, which is more difficult due to lower contrast and consistency (28). Discontinuities result from pavement marking wear or location where traffic diverges (i.e., exit ramps). Another particular concern is overlapping markings that occur when markings are re-painted, but some evidence of the former markings remain as shown in Figure 1. Pavement sealing may also create contrast with existing pavement which may be misinterpreted as a pavement marking. Additionally, the presence of objects on the pavement that show contrast have been shown to lead to incorrect lane choice decisions in some level-2 AV systems, even leading to driving in the opposing lanes of traffic (29).

Although uniform standards for pavement markings have not yet been established, research findings suggest 6-inch pavement markings provide more robust machine vision detection especially in situations where visibility is reduced, such as worn markings, wet conditions, and skip lines at high speeds (25). The US state, Michigan, included 6-inch edge lines on freeways (2020) and are implementing these on state trunklines. Wide dotted extension lines are also placed on exit and entrance ramps to improve lane guidance as part of MDOT's annual restriping program. MDOT started with non-freeways in 2021 for both white and yellow markings and estimates it will take 3 to 4 years to complete (30). The US state of Georgia has deployed lane striping technology (3M's Connected Roads All Weather Elements) along a stretch of I-85. The marking has tiny reflective beads embedded in the striping making the markings more vision to both human drivers and vehicles equipped with ADAS. The 13-mile project was a public-private partnership between the Georgia DOT and 3M (31). The US state of California began addressing pavement markings on a wide scale for CAVs by using six-inch pavement markings moving forward. They plan to transition the state's roughly 50,000 highways and interstates within the next two to three years, with most of the work being done during regular maintenance and construction work. Additionally, California has begun using more durable pavement markings (32). US state Colorado developed a statewide plan to upgrade markings to 6-inches and Kentucky and Iowa have adopted 6-inch standard for primary highways. New Hampshire is using 6-inch markings and added dotted edge line extensions across ramps. The US state Washington adopted a 6-inch standard for the eastern section of the state and 4-inch-high build waterborne markings for the western section of the state (25).

Other recommendations for standardization of pavement markings (33):

- Develop uniform markings for gore areas (in the US, there is no consensus for patterns in gore areas)
- Develop uniform contrast marking patterns (in the US, there are many different contrast patterns, for instance Skip Dashes where both white and black markings are used (34)
- Develop consensus on delineation of special lanes (i.e., HOV, bike lanes)

4. Signing

The first generation of CAVs use optical cameras for traffic sign recognition (TSR). As a result, the vehicle has to first notice and then interpret the lettering, symbol, or other sign characteristics (35). Although a number of approaches exist for TSR, the process primarily consists of three stages. The first is region segmentation where color is recognized, next shape analysis classifies the sign into primary shapes (i.e., circle, rectangle), and the third stage identifies class and meaning (36). Machine-vision systems are used to classify the sign using feature extraction and then match the information to a library of images to identify the sign message (37). Neural networks evaluate differences such as differences in angles, sign condition, light levels, and weather conditions. The more traffic control devices a vehicle "sees", the more it is able to store and interpret differences. However, the more standard a sign is, the more likely a vehicle is to correctly identify the sign.

Roper et al (38) evaluated TSR under real world conditions in Australia. One key finding was that electronic signs could not be consistently read by TSR which may be due to differences in illumination, refresh rate, sign size, height, and approach angle. They also noted TSR systems could not handle significant variations in sign maintenance. For instance, different levels of retro reflectivity or color. They also noted that when signs placed for minor roads were visible from the main roadways, they were incorrectly interpreted as belonging to the main roadway. Clusters of signs resulted in inconsistent readings by the systems. The systems also had some issues interpreting advisory signs as regulatory signs. They also found signs activated by flashing lights were not recognized.

Others have noted similar issues. The most cited concern with signing is consistent application (39). This entails placing signing at consistent locations, heights, and angle. For instance, curve warning signs or chevrons are not always placed the same from location to location. As a result, a curve with a certain radius may be signed in one location and not another. It has also been suggested signs be installed on both sides of the road and in standard locations. Speed limit signs should be placed to ensure they are clearly associated with the corresponding lane or roadway (25). Consistent refresh/flicker rates are also needed so they can be more easily detected and identified by CAV (33). The refresh rate of light-emitting diodes (LEDs) should be greater than 200 Hz to be easier for the vehicle's camera to detect. If the refresh rate is standardized for all electronic signs, then AV systems will be able to detect them much easier (25).

Although the US follows the Manual on Uniform Traffic Control Devices (MUTCD), a number of variations still exist in signs that have similar meanings. Additionally, many agencies in the US have developed signs that are not in the MUTCD which results in lack of standardization or have signs that may have been installed prior to the current MUTCD regulations. Having high levels of retroreflection is often cited as a need by the AV industry but not quantified. On the other hand, some AV industry stakeholders have reported situations where too much retroreflectivity blinded sensors. However, no suggested standard is available.

Figure 2: Sign Occluded by Vegetation (Image source: FWHA)

Consistency also entails ensuring signs are in similar conditions (33). Sign maintenance is important since faded or damaged signs are hard for both human and CAVs to read. Vegetation management is also important since vegetation occludes the sign from detection by sensor technologies as shown in Figure 2. Carlson (25) noted having high levels of retroreflection is often cited as a need by the AV industry (although not quantified).

As CAV systems become more sophisticated, it is expected the systems will need enhanced signs that offer redundancies in case one component, such as GPS, fails (40). Additionally, the infrastructure will need to support both human and machine vision for some time, requiring signing that is visible to humans and machines in any road conditions (41).

5. Traffic Signals

Recognition of traffic signal presence and state is more complicated than for pavement markings and signing but less information is available. The US National Committee on Uniform Traffic Control Devices (NCUTCD) conducted a survey of the automotive industry to support AV deployment and made the following recommendations for traffic signals (42, 43):

- Signals should be uniformly placed, horizontal traffic signals are particularly problematic as shown in Figure 3.
- Signals should be standardized including: position, location, color, shape, and refresh rate
- Backplates may be beneficial for east/west placement particularly in low sun conditions
- Signals should have a clear, unambiguous association with a specific lane
- High and low brightness should be standardized
- A 12-inch diameter signal head is preferred over an 8- inch
- Signals that target different classes of vehicles (i.e., cyclist or bus signals) should be placed and located at sufficient distance from each other so their individual applications can be differentiated
- Use green light rather than flashing beacons where possible (i.e., pedestrian crossing control is better as standard green-yellow-red light rather than flashing red). “Stop” and “go” directives should be explicit

Figure 3: Example of Inconsistent Signal Placement (Image source: Shutterstock)

6. Discussion

Although, the timeline for advanced CAVs becoming a significant portion of the fleet of vehicles on the roadway is still somewhat uncertain, local transportation agencies need to plan to accommodate them. Additionally, ADAS systems based on the technologies described in this paper are currently available and are increasingly becoming standard on all new vehicles (IIHS, 2020) leading to an immediate need for considering the potential impacts and benefits of accounting for these systems when planning and allocating resources. Local agencies can conduct future proofing by understanding the main infrastructure needs that CAV have and then integrating those needs into maintenance practices. General conclusions for how agencies can conduct early future proofing include:

- Pavement Markings: The main conclusion for how agencies can best address pavement markings in the short term is to place lane lines immediately after resurfacing, maintain quality lane lines, and move towards 6-inch lane lines. Some agencies are also using contrast pavement markings. Other suggestions include extension of lines through discontinuities.
- Signing: The main recommendation for signing is to maintain signs in good condition/retroreflectivity and ensure signs are not blocked. Constituency and standardization are also key recommendations, which includes sign message, placement, application, and maintenance.
- Traffic signals: The main recommendations also include consistency in position, location, color, shape, and brightness. Preference is for vertical signal placement and larger signal heads.

Future research is needed to understand the interactions and impacts between the CAV technologies and the real-world impacts of safety and traffic operations. Having specific estimates and models for this will allow agencies to make informed decisions, communicate better with policy makers and the public, and determine the best course for future proofing their assets and maintenance practices.

7. Acknowledgment

The authors wish to thanks to the Minnesota Department of Transportation (MnDOT) for funding this research along with the excellent Technical Advisory Panel members for their input and guidance. Additional information is provided in a report by the authors (44).

8. References

1. Sternlund, S., J. Strandroth, M. Rizzi, A. Lie, & C. Tingvall. The effectiveness of lane departure warning systems—A reduction in real-world passenger car injury crashes. Traffic injury prevention. 2017. 18(2): p. 225-229.
2. Cicchino, J. B. Effects of lane departure warning on police-reported crash rates. Journal of safety research. 2018a.,66: p. 61-70.
3. Flannagan, C., D. LeBlanc, R. Kiefer, S. Bogard, A. Leslie, C. Zagorski, & C. Beck. Field Study of Light-Vehicle Crash Avoidance Systems: Automatic Emergency Braking and Dynamic Brake Support. No. DOT HS 812 615. United States. Department of Transportation. National Highway Traffic Safety Administration. 2018.
4. Liu, J., K. Kockelman, & A. Nichols. Anticipating the emissions impacts of smoother driving by connected and autonomous vehicles, using the MOVES model. Transportation research board 96th annual meeting. 2017.
5. Qin, Y., H. Wang, & B. Ran. Stability analysis of connected and automated vehicles to reduce fuel consumption and emissions. Journal of Transportation Engineering, Part A: Systems. 2018. 144(11), 04018068.
6. Agashe, N. & S. Chapman. Traffic Signs in the Evolving World of Autonomous Vehicles. AveryDennison.com. Retrieved December 28, 2021, from Avery Dennison Reflective Solutions
7. Image Quality Factors. What is contrast detection probability? image-engineering.de. 2020. https://www.image-engineering.de/library/image-quality/factors/1075-contrast-detection-probability-cdp
8. Tesla. Autopilot. Tesla.Com. Retrieved December 29, 2021, from https://www.tesla.com/autopilot
9. Lutkevich, B. Self-Driving Car. SearchEnterpriseAI. 2019. searchenterpriseai.techtarget.com/definition/driverless-car
10. Li, Y., & J. Ibanez-Guzman. Lidar for autonomous driving: The principles, challenges, and trends for automotive lidar and perception systems. IEEE Signal Processing Magazine. 2020. 37(4): p. 50-61.
11. Wallace, A., A. Halimi, & G. Buller. Full waveform LiDAR for adverse weather conditions. IEEE transactions on vehicular technology. 2020. 69(7), p. 7064-7077.

12. Argo. Breakthrough New Lidar Technology Gives the Edge in Autonomous Delivery and Ride-Hail Services. Argo AI. Retrieved December 29, 2021, from https://www.argo.ai/company-news/breakthrough-new-lidar-technology-gives-argo-ai-the-edge-in-autonomous-delivery-and-ride-hail-services/
13. Hyundai. How do self-driving cars work? August 2018. www.hyundai.news/eu/articles/stories/how-do-self-driving-cars-work.html
14. Yoshida, J. Signal interference compromises automotive radar safety. Embedded.Com. Retrieved May 2021. www.embedded.com/signal-interference-compromises-automotive-radar-safety
15. Buller, W., B. Wilson, J. Garbarino, J. Kelly, N. Subotic, B. Thelen, & B. Belzowski. Radar congestion study (Report No. DOT HS 812 632). Washington, DC: National Highway Traffic Safety Administration. 2018.
16. Continental. Continental Automotive. ARS540. 2021. https://www.continental-automotive.com/en-gl/Passenger-Cars/Autonomous-Mobility/Enablers/Radars/Long-Range-Radar/ARS540
17. English, T. How do Self Driving Cars Work. Interesting Engineering. January 11, 2020. interestingengineering.com/how-do-self-driving-cars-work.
18. Carlson, Paul. How Automated Vehicles will change Pavement Markings. Pavement Maintenance. ForConstructionPros. January 2019. https://www.forconstructionpros.com/pavement-maintenance/article/21036066/road-marking-for-automated-vehicles
19. Moylan, M. Technology Around Self-Driving Cars Drives Forward, But Future Still Uncertain. Business. MPR News. 2018. www.mprnews.org/story/2018/03/26/self-driving-cars-technology-drives-forward-future-uncertain.
20. Knight, R. Paving the Way for Driverless Cars. Inside Unmanned Systems. 2016. http://insideunmannedsystems.com/paving-the-way-for-driverless-cars/.
21. PPP. PPP Transportation Safety Innovations: Product and Reference Guide. Professional Pavement Products Company, Jacksonville, FL. 2018. https://pppcatalog.com/wp-content/uploads/2018/08/PPPTSI-Catalog.pdf.
22. Intertraffic. Machine Vision and Contrast How Automated Vehicles See The Roads. May 2019. www.intertraffic.com/news/autonomous-driving/machine-vision-and-contrast-how-automated-vehicles-see-the-roads/
23. Davies, C. Pavement Markings Guiding Autonomous Vehicles – A Real World Study. Potters Industries. 2016. higherlogicdownload.s3.amazonaws.com/AUVSI/14c12c18-fde1-4c1d-8548-035ad166c766/UploadedImages/documents/Breakouts/20-2%20Physical%20Infrastructure.pdf
24. Burghardt, T., R. Popp, B. Helmreich, T. Reiter, G. Bohm, G. Pittere, & M. Artmann. Visibility of Various Road Markings for Machine Vision. Case Studies in Construction Materials. 2021. Vol. 15. E00579.
25. Carlson, P. Traffic Control Devices: Considerations to Support Automated Vehicle Deployment. Transport Canada. April 2021. https://propulsionquebec.com/wp-content/uploads/2021/05/Traffic_Control_Devices_-_Considerations_to_Support_Automated_Vehicle_Deployment_1_.pdf?download=1
26. Schwab, K.. The Quest to Design A Smarter Road. Fast Company. 2017. www.fastcompany.com/90140902/smart-roads-are-coming-do-we-need-them.
27. O'Keefe, L. New Kinds of Street Signs and Highway Markings Can Talk to Autonomous Vehicles. Bisnow National. 2017. www.bisnow.com/national/news/technology/new-kinds-of-street-signs-and-highway-markings-can-talk-to-autonomous-vehicles-79921.
28. RSMA. UK Roads Insufficient for Autonomous Vehicles. 2017. Road Safety Markings Association, Gainsborough, Lincolnshire, UK.
29. Tencent Keen Security Lab. Experimental Security Research of Tesla Autopilot. 2019. https://keenlab.tencent.com/en/whitepapers/Experimental_Security_Research_of_Tesla_Autopilot.pdf
30. MDOT. Six-Inch-Wide Pavement Markings. Michigan Department of Transportation. Accessed December 2021. www.michigan.gov/mdot/0,4616,7-151-9615_11261-548292--,00.html
31. Roads&Bridges. Update: Lane Markings on Georgia Interstate to Improve Testing of Autonomous Vehicles. January 2020. www.roadsbridges.com/update-lane-markings-georgia-interstate-improve-testing-autonomous-vehicles
32. Ayre, J. Caltrans Is Already Modifying California's Roads for Self-Driving Cars. Clean Technica. 2017. cleantechnica.com/2017/07/25/caltrans-already-modifying-californias-roads-self-driving-cars.
33. Gopalakrishna, D., P. Carlson, P. Sweatman, D. Raghunathan, L. Brown, & N. Serulle. Impacts of Automated Vehicles on Highway Infrastructure. U.S. Department of Transportation,
Federal Highway Administration. FHWA-HRT-21-015. March 2021.
34. IowaDOT. New paint process improves safety for workers and motorists - Transportation Matters for Iowa | Iowa DOT. Iowadot.Gov. 2020. https://www.transportationmatters.iowadot.gov/2020/07/new-paint-process-improves-safety-for-workers-and-motorists.html
35. McMahon, J. 7 Ideas to Pave the Way for Autonomous Vehicles. Forbes. 2018. www.forbes.com/sites/jeffmcmahon/2018/04/09/7-ways-the-roads-can-get-ready-for-autonomous-vehicles/#25548fdf43dd.

36. Wahyono, L., J. Hariyono, & K. Jo. Traffic Sign Recognition System for Autonomous Vehicle Using Cascade SVM Classifier. IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society. 2014, p. 4081-4086.
37. Snyder, J., D. Dunn, J. Howard, T. Potts, & K. Hansen. “Invisible” 2D Bar Code to Enable Machine Readability of Road Signs – Material and Software Solutions. 2018. 3M Transportation Safety Division, St. Paul, MN. https://multimedia.3m.com/mws/media/1584051O/2d-barcode-whitepaper.pdf.
38. Roper, Y., M. Rowland, Z. Chakich, W. McGill, V. Nanayakkara, D. Young, & R. Whale. Implications of Traffic Sign Recognition (TRS) Systems for Road Operators. Austroads, LTD. AP-R580-18. August 2018.
39. FHWA. Global Automakers. FHWA Automated Driving Systems: Request for Information, Docket Number FHWA-2017-0049. 2017.
40. Veoni, D. Self-Driving Cars are Coming, but US Roads Aren’t Ready for the Change. The Hill. http://thehill.com/opinion/technology/353034-self-driving-cars-are-coming-but-us-roads-arent-readyfor-the-change. September 2017.
41. 3M. Products for Automated Driving: The Next Evolution of Intelligent Infrastructure. 2018. www.3m.com/3M/en_US/transportation-infrastructure-us/solutions/automated-driving.
42. NCUTCD. National Committee on Uniform Traffic Control Devices – CAV Joint Task Force Survey of Automotive Manufacturers, February 2019.
43. PATH. Autonomous Vehicles Industry Survey of Transportation Infrastructure Needs, Draft Final Project Report, Prepared by California Partners for Advanced Transportation Technology (PATH), February 2021.
44. Hallmark, S., D. Veneziano, & T. Litteral. Preparing Local Agencies for the Future of Connected and Autonomous Vehicles. Minnesota Department of Transportation. MN/RC 2019-18. May 2019. http://www.dot.state.mn.us/research/reports/2019/201918.pdf