CHAPTER FOUR

Brief History and Current State of Autonomous Vehicles

In this chapter, we review the history of AV technology and the technology's status as of July 2013. Our goal is to provide a nontechnical summary of the technology and its limitations for an interested policy audience. The current state of technology in particular is relevant for several near-term policy decisions:

- Will states need to regulate AV models that may each have different operating limitations—and, if so, how?
- What kinds of safety testing and verification will be required before the first AV is commercially available?
- What near-term actions can state and federal transportation agencies take to increase the safety of AVs, given their financial constraints and the uncertainty in the development of AVs?

A Brief History

Visions of AVs and automated highways in the mid–20th century remained largely in the eye of futurists and science fiction enthusiasts. In 1958, for example, Disney aired a program titled "Magic Highway USA" that imagined a future with, among other technologies, AVs guided by colored highway lanes and operated with addresses coded on punch cards. It was not until the mid-1980s that the underlying computing and other technologies needed to realize (and revise) these visions truly became available. The advances made in the last 25 years can be understood in terms of three successive waves of developmental gains.

Phase 1: Foundational Research

From approximately 1980 to 2003, university research centers, sometimes in partnership with transportation agencies and automotive companies, undertook basic studies of autonomous transportation. Two main technology concepts emerged from this work.

As one thrust, researchers pursued the development of automated highway systems, in which vehicles depend significantly on the highway infrastructure to guide them. One of the first major demonstrations of such a system took place in 1997, over a 7.6-mile stretch of California's I-15 highway near San Diego. Led by the California Partners for Advanced Transit and Highways (PATH) program, the "DEMO 97" program demonstrated the platooning of eight AVs guided by magnets embedded in the highway and coordinated with vehicle-to-vehicle (V2V) communication (Ioannou, 1998).

A second research thrust was to develop both semi-autonomous and autonomous vehicles that depended little, if at all, on highway infrastructure. In the early 1980s, a team led by Ernst Dickmanns at Bundeswehr University Munich in Germany developed a vision-guided vehicle that navigated at speeds of 100 kilometers per hour without traffic (Lantos and Mâarton, 2011). Carnegie Mellon University's NavLab developed a series of vehicles, named NavLab 1 through NavLab 11, from the mid-1980s to the early 2000s. In July 1995, NavLab 5 drove across the country in a "No Hands Across America" tour, in which the vehicle steered autonomously 98 percent of the time while human operators controlled the throttle and brakes. Other similar efforts around the world sought to develop and advance initial AV and highway concepts.

Phase 2: Grand Challenges

From 2003 to 2007, the U.S. Defense Advanced Research Projects Agency (DARPA) held three "Grand Challenges" that markedly accelerated advancements in AV technology and reignited the public's imagination. The first two Grand Challenges charged research teams with developing vehicles that were fully autonomous for competition in a 150-mile off-road race for $1 million and $2 million prizes, respectively. No vehicle completed the 2004 Grand Challenge—the best competitor completed less than eight miles of the course ("Desert Race Too Tough for Robots," 2004). However, five teams successfully completed the 2005 Grand Challenge course, held a mere 18 months later. The fastest team completed the course in just under seven hours, with the next three fastest vehicles finishing within the next 35 minutes (DARPA, undated).

In 2007, DARPA held its third and final AV challenge, dubbed the "Urban Challenge." As the name suggests, vehicles raced through a 60-mile urban course, obeying traffic laws and navigating alongside other autonomous and human-driven vehicles. Six teams finished the course, and three completed the race within a time of 4.5 hours, including time penalties for violating traffic and safety rules. This Grand Challenge spearheaded advancements in sensor systems and computing algorithms to detect and react to the behavior of other vehicles, to navigate marked roads, and to obey traffic rules and signals.

Phase 3: Commercial Development

The DARPA Challenges solidified partnerships between auto manufacturers and the education sector, and it mobilized a number of endeavors in the automotive sector to advance AVs. These include the Autonomous Driving Collaborative Research Lab, a partnership between GM and Carnegie Mellon University (Carnegie Mellon University, undated) and a partnership between Volkswagen and Stanford University (Stanford University, undated).

Google's Driverless Car initiative has brought autonomous cars from the university laboratory into commercial research. The program began shortly after the DARPA Urban Challenge and drew upon the talents of engineers and researchers from several teams that participated in that competition. In the years since, Google has developed and tested a fleet of cars and initiated campaigns to demonstrate the applications of the technology through, for example, videos highlighting mobility offered to the blind (Google, 2012). Google is not alone. In 2013, Audi and Toyota both unveiled their AV visions and research programs at the International Consumer Electronics Show, an annual event held every January in Las Vegas (Hsu, 2013).

State of Autonomous Vehicle Technology

As of March 2013, Google alone had logged more than 500,000 miles of autonomous driving on public roads without incurring a crash attributable to the technology.[1] Numerous technological breakthroughs have made these achievements possible, including advanced sensors to gather information about the world, increasingly sophisticated algorithms to process sensor data and control the vehicle, and more computational power to run them in real time.

AVs like Google's that drive on public roads are currently operated by specially trained human operators who take control of the vehicle in dangerous or unexpected conditions, including roadwork, inclement weather, and near crashes. Ultrareliability seems a prerequisite for vehicles that are fully autonomous—i.e., vehicles in which the driver plays no role in the driving task, and for driverless cars, which may have no driver in the vehicle at all. Such reliability is extremely difficult to achieve in a dynamic and complex environment in which many factors fall beyond the control of vehicle designers or operators.[2] Yet, such capabilities may be necessary if AVs are to deliver on their potential of being extremely safe, light, and efficient vehicles; of offering mobility to those who lack it; of creating new models of vehicle ownership and new land-use patterns; and of reshaping commerce. In this section, we briefly discuss current AV technology, its limitations, and possible ways forward.

Making Sense of the World

In the most general terms, AVs employ a "sense-plan-act" design that is the foundation of many robotic systems.[3] A suite of sensors on the vehicle gathers raw data about the outside world and the vehicle's relation to its environment. Software algorithms interpret the sensor data—e.g., lane markings from images of the road, behavior of other vehicles from

[1] In 2011, a Google AV was involved in a minor crash, but a human driver was operating it at the time (Yarrow, 2011).

[2] By way of contrast, commercial aircraft operate in a much simpler environment and, among other things, make use of air traffic control for guidance and coordination with other aircraft.

[3] See, generally, Siciliano and Khatib (2008).

radar data. They use these data to make plans about the vehicle's own actions—its overall trajectory down the road and immediate decisions such as accelerating and changing directions. These plans are converted into actionable commands to the vehicle's control system; i.e., steering, throttle, brakes. Many "sense-plan-act" loops may run in parallel on an AV. One loop may run at extremely high frequency to initiate rapid emergency braking, while another runs less frequently to plan and execute complex behaviors such as changing lanes. In some cases, the planning component of the loop is extremely short and resembles a sense-act cycle instead of a sense-plan-act cycle. For instance, a vehicle may gather data about obstacles immediately in front of it at very high frequency and initiate emergency braking if any obstacle is detected within a short distance. In this case, the sensor data may directly trigger a vehicle action.

With perfect perception (a combination of sensor data gathering and interpretation of those data), AVs could plan and act perfectly, achieving ultrareliability. Vehicles never tire; their planning algorithms can choose provably optimal behaviors; and their execution can be fast and flawless.[4] For example, if a deer were to leap into the path of a human-driven vehicle, the driver may make mistakes in choosing whether to swerve, brake, or take another course of action. The driver may also make mistakes in executing the action; e.g., oversteering a swerve. AVs need never make these mistakes. Computer algorithms can rapidly evaluate, compare, select, and execute the best action from among a number of maneuvers, taking into account the vehicle's speed, the animal's trajectory, the position and behavior of other vehicles, and the utility of various outcomes.

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[4] Not all robotic behaviors are as well developed as vehicle navigation, which has been studied for decades. Other actions are difficult for robots to perform, such as folding an item of clothing or separating the filling from an Oreo cookie. Both have received significant research attention. While these manipulation tasks include challenging perception problems, they additionally require planning with many more degrees of freedom and with difficult constraints on the robot. As such, they cannot rely on traditional planning algorithms, which often involve two or three dimensions (Cusumano-Towner et al., 2011; Hornyak, 2013).

One of the more difficult challenges for AVs is making sense of the complex and dynamic driving environment—e.g., perceiving the deer. The driving environment includes many elements:

- other vehicles on the road, each of which operates dynamically and independently
- other road users or on-road obstacles, such as pedestrians, cyclists, wildlife, and debris
- weather conditions, from sunny days to severe storms
- infrastructure conditions, including construction, rough road surfaces, poorly marked roads, and detours
- traffic events, such as congestion or crashes.

It is in making sense of the world that humans often outperform robots. Human eyes are sophisticated and provide nearly all of the sensory data we use to drive. We are also adept at interpreting what we see. Although our eyes are passive sensors, only receiving information from reflected light, we can judge distances; recognize shapes and classify objects such as cars, cycles, and pedestrians; and see in a tremendous range of conditions. Of course, we are far from perfect. Our sight and our cognition of visual information vary and can be dangerously limited in several situations: adverse ambient conditions such as darkness, rain, and fog; when we are tired or distracted; and when we are impaired through the use of drugs or alcohol (Olson, Dewar, and Ferber, 2010).

Camera-based systems, i.e., computer vision systems, are the analogy to human eyes and visual cognition. They can “see” very long distances and provide rich information about everything in their field of view. Cameras are also inexpensive, making them important components for cost-effective autonomy. However, they have two important limitations. First, the underlying algorithms are not nearly as sophisticated as humans at interpreting visual data. The Solutions in Perception Challenge is an annual competition that embodies this difference, challenging engineering teams to develop computer vision and other sensor algorithms that can detect, recognize, and locate objects. In the 2011 competition, for example, the objects included a number of items that would be found on supermarket shelves. None of the competing teams reached the goal of 80 percent accuracy (Markoff, 2011).

A second limitation is that, like human eyes, camera systems are better able to gather data in some ambient conditions (e.g., clear sunny days) than others (e.g., fog or rainstorms). Changes in ambient conditions also pose challenges, as camera systems calibrated to certain conditions may have difficulty interpreting data in others. This problem of autonomous camera calibration is also a fundamental robotics research problem (Furukawa and Ponce, 2009).

Of course, AVs have a critical advantage over humans: they can draw upon a much wider array of sensor technologies than cameras alone.[5] While many major advances have been made in the last decade, interpretation of visual data (and sensor data more generally) remains a fundamental research problem in the field of computer vision. We can expect advances in both sensor technology and perception algorithms, but matching human perception under best conditions is a long-term research challenge. Here, we review a few of the most widely used sensors, besides cameras, for driver assistance and AVs.

Sensor Systems

Light detection and ranging, or *lidar*, systems feature prominently in robotic systems, including AVs. Lidar systems determine distances to obstacles by using laser range finders, which emit light beams and calculate the time-of-flight until a reflection is returned by objects in the environment. Many sophisticated lidars couple multiple laser range finders with rapidly rotating mirrors to generate three-dimensional point clouds of the environment. Developed during the DARPA Grand Challenges and used by teams in the Urban Challenge and by Google, the Velodyne HDL-64E lidar uses 64 lasers that provide 1.3 million data points per second and offer a 360-degree field of view. Lidars are typically useful over a shorter range than other sensors—the Velodyne provides data up to 120 meters away, depending on the reflectivity of the object. Lidar systems' two key limitations are

[5] This is the aim of increasingly prevalent driver assistance systems that provide the driver with data and warnings about the driving environment, e.g., rear-facing cameras and radar sensors that warn the driver when an obstacle is in the vehicle's path.

range (less useful at long ranges) and reflectivity (poor reflection off of certain kinds of materials). The Velodyne's specifications state that it detects black asphalt, which has low reflectivity, to a range of just 50m (Velodyne, 2010). The costs of lidar systems range widely but are expected to decline in the near future. Google originally paid approximately $70,000 for the lidar system on a single vehicle, including a Velodyne lidar. However, the German lidar manufacturer Ibeo has stated it will provide lidar systems for $250 per vehicle in 2014 (Priddle and Woodyard, 2012).

Radio detection and ranging, more commonly known as *radar*, is another key sensor for AVs. Like lidar, radar systems use signals' time of flight to determine the range to objects in the environment. Unlike lidar, radar uses radio waves, which give radar systems different capabilities and limitations. The reflectivity limitations of radar are typically even more severe than those of lidar: It works well on metallic objects, such as vehicles, but nonmetallic objects, such as pedestrians, are essentially invisible to a radar sensor. Pedestrian detection using radar has become a key area of research in automotive radar, given increasing use in driver assistance systems (Panasonic, 2012). Radar systems used for ACC can currently add approximately $1,000 to the price of vehicles, though manufacturers are continuing efforts to reduce sensor cost (Stevenson, 2011).

In addition to cameras, lidar, and radar, a number of other sensors may be used to help vehicles make sense of the world around them. Ultrasonic sensors can provide accurate short-range data (1–10 meters), which makes them useful for parking assistance systems and backup warning systems (Ford, 2013). They are also relatively inexpensive, with after-market solutions retailing for as little as $120. Infrared systems are capable of detecting lane markings without the lighting and environmental limitations of cameras. However, the range for this purpose is very small, making the systems more useful for detecting lane departures than for tracking lanes (Mathas, 2013). Infrared sensors may also be useful for detecting pedestrians and bicycles, particularly at night.

Sensor Suites

As this review suggests, each sensor provides different kinds of data and has its own limitations related to field of view, ambient operating conditions, and the elements in the environment that it can sense. Because the limitations of these sensors are fairly well understood, the usual practice is to construct suites of complementary sensors that are positioned around the vehicle to prevent blind spots—both visual blind spots (i.e., due to occluded views) and material blind spots (i.e., the inability to detect certain kinds of objects or certain properties of objects in the environment). Sensors can also be integrated to perceive more about the environment than can be learned purely from the sum of individual sensors' data. As one example, vision can detect colors of surfaces in the distance while lidar can be used to determine the material as that surface approaches. When coupled, a system can learn that green surfaces in the distance correspond to grass, allowing the vehicle to make greater sense of the environment that is far away (Thrun et al., 2007).

Vehicles also use sensor suites for localization, i.e., determining their own position in the world. The use of the global positioning systems (or GPS) is essential for localization. Vehicle GPS systems receive signals from orbiting satellites to triangulate their global coordinates. These coordinates are cross-referenced with maps of the road network to enable vehicles to identify their position on roads. The accuracy of GPS systems has improved significantly since 2000, when the U.S. government made GPS fully available to civilian users.[6] However, GPS error can still be large—several meters, even under ideal conditions. The errors grow rapidly when obstacles or terrain occlude the sky, preventing GPS receivers from obtaining signals from a sufficient number of satellites. This is a significant concern in urban areas, where skyscrapers create "urban canyons" in which GPS availability is severely limited.

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[6] Prior to 2000, GPS used a system called "Selective Availability" that provided civilian applications with a degraded signal with lower accuracy than the military-grade signal. In May 2000, an executive order by President Bill Clinton (Exec. Order No. 12866) ended Selective Availability and provided civilian users the same quality signal as military users (National Coordination Office for Space-Based Positioning, Navigation, and Timing, 2014).

GPS is typically coupled with inertial navigation systems (INS), which consist of gyroscopes and accelerometers, to continuously calculate position, orientation, and velocity of a vehicle without need for external references. INS are used to improve the accuracy of GPS and to fill in "gaps" such as those caused by urban canyons. The key challenge with INS is drift—even over very short time periods, small errors can aggregate into large differences between calculated and true positions. For example, a 10-second period during which the system relies on INS because the GPS signal is unavailable can result in more than a meter of drift in calculated position, even with some of the most sophisticated systems (Applanix, 2012).

Thus, even these systems can result in inaccurate positioning. Many AVs therefore draw on prebuilt maps, which can come in many forms. For example, in the DARPA Urban Challenge, teams were given "Road Network Definition Files" that encoded approximate GPS coordinates for the course's road segments, stop signs, and waypoints. Many teams also manually corrected the definition files with aerial imagery of the road network to achieve more accurate positioning. Thus, vehicles could correct the error in their local pose estimates by correlating the location of features in the definition files with features they observed in the environment (Buehler, Iagnemma, and Singh, 2010). It may be difficult to construct and maintain highly accurate maps of all connected roads. This could limit the routes on which AVs drive.

Different combinations of sensors offer different combinations of capabilities and redundancies at different price-points, and cost is a key constraint. While every additional sensor may contribute some degree of navigational assistance in a particular set of conditions, it also increases the physical and computational complexity and cost of the vehicle, and decreases the feasibility of its introduction in commercial vehicles. Many sensor manufacturers are offering less sophisticated and lower-cost sensors tailored to particular needs.[7]

[7] As one example, Velodyne began offering a lidar with 32 lasers instead of 64 in response to customer demands for smaller size and lower cost ("Velodyne's LiDAR Division Doubles Production Capacity to Meet Demand," 2013).

There are also efforts to develop autonomous systems that use just a few low-cost sensors, but these systems have more operational limitations. MobilEye Vision Technologies, for example, has developed an AV that uses only cameras to drive in a single lane at highway speeds and identify and respond to traffic lights. “The idea is to get the best out of camera-only autonomous driving,” noted one of MobilEye’s executives (Markoff, 2013). Similarly, the winner of the 2013 Intel International Science and Engineering Fair, a 19-year-old student from Romania, developed an AV system design using radar and cameras at a cost of $4,000 per vehicle (Intel.com, 2013). At this point, it is not clear if there is a single suite of sensors that will emerge as the best tradeoff between the constraints of robustness of sensing and cost.

Environmental Challenges

Other challenges pose significant concerns. Certain ambient conditions (e.g., severe precipitation, dense fog) may pose problems for multiple sensors simultaneously. Common failure conditions such as this limit the extent to which sensor combinations can compensate for individual sensor limitations. It must be noted, however, that these same conditions pose problems for humans. Indeed, robotic sensors such as radar may prove more effective than human vision, and the rapid reaction of planning algorithms may be particularly valuable, making autonomous systems imperfect but potentially safer than human drivers in these adverse conditions.

Terrain also poses challenges. A sensor configuration appropriate for a flat environment may be inappropriate for steep hills, where sensors must look “up” or “down” slopes. Different terrain can require different sensor configurations, which may not be readily changeable. While sensors can be put on adjustable mounts to accommodate this problem, this adds complexity and cost (Urmson, Ragusa, et al., 2006).

Road materials also change from region to region. They are typically concrete and asphalt, but can be made of dirt, cobblestone, and other materials. Different materials have different reflectivity, and sensors calibrated to certain materials may have difficulty detecting other materials with equal fidelity.

Construction projects and roadwork are particularly difficult to negotiate, as there may be little consistency in signage and alerts, roadway materials may change suddenly and the maneuvers needed to navigate through construction zones may be complex and poorly marked. Moreover, these areas often involve deviations from preconstructed maps, so vehicle localization may be particularly difficult.

Each of these factors can have implications for where AVs can or cannot successfully operate. Weather and terrain vary significantly across the United States, as do the road materials and signage practices used by DOTs and other agencies. A vehicle that operates easily on flat terrain in Louisiana may have significant performance challenges on Colorado's snowy and steep roads, or in New York City's congested urban canyons.

Graceful Degradation

Sensor failure (as opposed to external environmental conditions) can also pose serious performance threats (Hwang et al., 2010). Sensors may fail because of electrical failures, physical damage, or age. It will be critical for AVs to have internal sensing and algorithms that can detect when internal components are not performing adequately. This is not easy. A sensor that fails to provide any data is easily detected as nonfunctioning, but a sensor that occasionally sends spurious data may be much harder to detect.

These and other failures will require a system that degrades gracefully (Berger and Rumpe, 2012). AVs will likely need to have an ultra-reliable and simple low-level system that uses minimal sensor data to perform basic functions in the event of main system degradation or failure. The backup system must also be able to detect degradation and failure and override control rapidly and safely. The task of graceful degradation may be complicated by traffic conditions and roadways. If a system fails in the middle of a curve in dense traffic, it may need to be able to navigate to a safe area to pull over.

V2V and V2I Communication

Clearly, there are many challenges to overcome before vehicles can accurately perceive the state of the environment from sensor systems. Many researchers and developers have suggested an alternative: What if the environment communicated its state to the vehicle? This is the motivation behind V2V and V2I communication, in which vehicles communicate with the surrounding infrastructure, with each other, or both. In doing so, they could receive information about hazardous conditions, such as icy roads or crashes; nonhazardous conditions, such as congestions; or route recommendations. They could also coordinate their behavior—for example, by taking turns through intersections or maintaining faster speeds and closer spacing on highways.

These approaches have received significant attention in federally funded efforts; e.g., through the research programs of the Research and Innovative Technology Administration's (RITA's) Intelligent Transportation System Joint Program Office (Intelligent Transportation Systems, 2013a). A key part of the federally funded research effort—in partnership with industry and academia—is aimed at developing standards for Dedicated Short-Range Communication (DSRC) (Intelligent Transportation Systems, 2013b), bandwidth allocated by the FCC for automotive use (FCC, 1999). This spectrum is capable of supporting safety applications that require nearly instantaneous communication (Strickland, 2013). DSRC can enable a communication network of nodes consisting of mobile vehicles or roadside units, sharing traffic and safety information and coordinating vehicle behavior.

However, V2V and V2I have practical challenges, as well as technological challenges. Creating, maintaining, and ensuring ultrareliability of public infrastructure for driverless cars may be prohibitively expensive, particularly in a time of growing fiscal uncertainty for transportation agencies. Additionally, to be safe and effective, V2V technologies require a critical level of deployment of vehicle communication technology, development of communication standards, and consistent application of those standards in platforms developed by different manufacturers. To coordinate behaviors, vehicles must also all be accurately localized before they can broadcast and coordinate their positions, velocities, and other features. There are also cybersecurity concerns. We discuss the issues raised by DSRC and communications more generally in Chapter Five.

Sharing the Drive

Partly as a result of all of the limitations listed above, a "shared driving" concept of operation is consistent with many expectations of the first commercially available AVs: vehicles can drive autonomously in certain operating conditions—e.g., below a particular speed, only on certain kinds of roads—and will revert to traditional, manual driving outside those boundaries or at the request of a human driver. Such shared driving conditions will depend little, if at all, on specially designed infrastructure or on the capabilities of other vehicles.

This approach poses its own challenges. One key challenge will be human driver reengagement. To experience most of the benefits of the technology, human drivers will need to be able to engage in other tasks while the vehicle is autonomously driving. For safety, however, they will need to quickly reengage at the request of the vehicle. Such context switching may need to occur fully and in a matter of seconds or less. Cognitive science research on distracted driving suggests this may be a significant safety challenge (Drews et al., 2009; Neubauer, Matthews, and Saxby, 2012). Finding the right balance between requiring the human to be ready to intervene at a moment's notice and realizing the benefits of this technology is likely to be a challenge.

For example, should the driver of a conditionally automated vehicle be encouraged or permitted to send a text or an email? Should the driver be able to watch a movie? And what should happen when humans almost inevitably rely too much upon the technology? Relatedly, there may be issues of consumer acceptance. While consumers may be willing to pay for a car that permits them to text or watch a movie while driving, they may be unwilling to pay much for automation that requires them to sit alert, hands on the wheel, ready to take over at any moment.

As with any other component of the driving system, the vehicle will need internal sensors to monitor the behavior of the human part of the system. Some have suggested a variety of mechanisms to ensure that the driver is sufficiently engaged—for example, a vibrating seat or wheel, or vehicle screens that show the road rather than entertainment. But while a vehicle manufacturer may carefully limit what is displayed on a vehicle's screen, it has little control over whether a consumer uses his own device to watch a movie or send messages. More active monitoring of the driver's behavior and attention is theoretically possible, but may be resisted by drivers.

The vehicle must also adapt gracefully when the human driver's performance is degraded; e.g., the driver is asleep or intoxicated. In these situations, the vehicle may refuse to engage in autonomous driving or fall back upon the backup system to bring the vehicle to a safe stop. This, in turn, may raise both engineering and privacy concerns. How will it be secure? With whom will it be shared? Will the data gathered about passengers be admissible evidence in trials? If the system mistakenly detects degraded driver performance, will there be a manual override? The legal implications of these technologies are complex and unclear.[8]

Similarly, developing the appropriate mental models for the collaboration necessary for automation Levels 2 and 3, where the driver needs to be prepared to take over, has yet to occur. While autopilots are familiar in both aviation and marine use, the marine and aviation contexts generally allow more time for transition between the autopilot and manual control—and in both cases, operators often receive extensive training about the capabilities and limitations of the systems.

Partly because many of the human-computer interaction issues outlined above are difficult, not everyone believes that Levels 2 and 3 autonomy and shared driving are the appropriate path. Some, for example, have advocated for fully autonomous, driverless vehicles that would travel at low speeds over a limited geographic area. Stanford University, for example, has plans to introduce a driverless shuttle on its campus, and the CityMobil 2 project in Europe will use low-speed driverless vehicles in a number of different European cities. Similarly, Singapore's Nanyang University plans to introduce a driverless low-

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[8] As one example, the OnStar system uses a two-way mobile phone link to provide navigation assistance, in-vehicle security, remote engine shut-off, and other features. Such a system could be used by law enforcement to monitor conversations in the vehicle, to track the vehicle, or to allow dealerships to immobilize vehicles whose owners are past due in their payment. In September 2011, OnStar, a General Motors product, announced that it would continue collecting data from vehicles even if owners were no longer paying for the service, and left open the possibility of sharing or selling anonymized data (Poulsen, 2010; Li, 2013).

speed shuttle on a 1.2-mile route (Coxworth, 2013). Such an approach sidesteps the difficult driver-computer interaction issues, though possibly at a cost of raising difficult pedestrian-computer interaction issues.

Integrity, Security, and Verification

AV software and hardware will be tested extensively, likely using many of the techniques used to test aircraft systems and other complex ultra-reliable systems. But virtually every consumer device, from cell phones to robotic vacuum cleaners, requires software upgrades. This creates software reliability challenges, as software upgrades may need to be backward-compatible with earlier models of vehicles and sensor systems. Moreover, as increasing numbers of vehicle models offer autonomous driving features, software and other system upgrades will have to perform on increasingly diverse platforms, making reliability and quality assurance all the more challenging.

Software upgrades highlight a broader concern with AVs: system security. Vehicles that are connected to each other, to infrastructure, or to the Internet are increasingly open to cyberattack. David Strickland, former head of NHTSA, has noted (2013):

> With this evolution comes increased challenges, primarily in the area of system reliability and cybersecurity—the latter growing more critical as vehicles are increasingly more connected to a wide variety of products . . . Whether the entry point into the vehicle is the Internet, aftermarket devices, USB ports, or mobile phones, these new portals bring new challenges.

Even primarily unconnected vehicles may be at risk. Software upgrades, for example, will likely require connection to the Internet, which creates the possibility of vehicles being attacked by computer viruses that corrupt the system; for example, a virus could enter the system by masquerading as a legitimate software upgrade. Preventing this requires extremely secure connections to upgrade servers and a number of "handshake" mechanisms to ensure that the source of upgrades—and the upgrades themselves—are legitimate and uncorrupted. Unchecked, malicious actors might be able to commandeer a single vehicle (or a fleet of vehicles) to commit crimes, or even acts of terrorism.

Software security is not the only concern. Vandals or criminals may use GPS jammers or send other interference signals to disrupt AV sensors or transmit false sensor readings to a vehicle's sensors; e.g., sending false lidar returns to a vehicle that is using three-dimensional mapping to navigate through its environment.[9] While this may be more difficult to achieve, it may also be more difficult to detect since spoofed sensor readings may appear legitimate.

Vehicle owners also pose possible security threats. Many technology enthusiasts seek access to their own systems to gain control over elements that are otherwise locked down by the manufacturer. The terms "jail breaking" and "rooting" refer to the act of breaching the built-in security for mobile phones (which is often accomplished through physical tampering) to provide the owner with greater access and flexibility; e.g., moving the phone from one carrier to another. AVs will surely be as big a temptation for "jail breaking" as users seek to improve performance or run their own software, almost certainly while risking safety. This will require manufacturers to ensure users cannot hack into the vehicle's hardware and software systems. It may also require states to perform annual inspections of the vehicle system's integrity.

A mobile communications provider we interviewed stated that security issues are not well understood. His concern was that, as vehicles become more computerized and more connected, they provide another aspect of critical infrastructure and a potential target for a cyberattack. He said all of an AV's systems ought to be designed to resist possible intrusion by hackers, citing an example where hackers were able to access a car's electronic systems through a seemingly innocuous system to monitor tire pressure. He said security measures need to apply to all communications paths into the car, whether it is Wi-Fi, cellular communications, or DSRC.

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[9] However, human drivers are not immune to such attacks and could be blinded by lasers or misled by false signs.

Like any technology, AVs will experience failures and breaches. The most critical feature will be the system's ability to detect failures and breaches and act safely—switching to a tightly controlled and simple safety system or refusing to engage at all.

Policy Implications

The variety of AV development efforts suggest that states may soon face the question of whether and how to regulate vehicles with different capabilities and operating limitations. Different manufacturers may take vastly different approaches to autonomous driving. Google, for example, seems to be pursuing a vehicle that is fully autonomous and capable of complex and general driving, while MobilEye seems focused on a narrower driving capability. The same manufacturer may offer different models or different capabilities in new versions of the same vehicle model. This has implications for state and national regulations, vehicle standards, liability, and near-term DOT investments. We touch on these issues briefly here, and discuss them further in later chapters.

Policymakers could regulate different specific vehicle capabilities: highway vs. city driving, fast vs. slow driving, fully autonomous vs. driver back-up capabilities. As stakeholder interviews suggest, it is likely prohibitively expensive for individual state or local agencies to develop and enforce numerous regulations tailored to specific operating conditions and capabilities.

Policymakers must also consider how to regulate the drivers of different AVs to ensure they understand how to safely operate and interact with the machines. This human factor is critical to the safety for vehicles that use a shared driving concept. Many states already require specific tests and certifications to drive motorcycles, for example, and they have limitations (principally age restrictions) on who may drive them. Regulations for drivers of AVs could take a similar approach, requiring additional practical tests to demonstrate drivers' operational competence. Yet, different AV models and capabilities may each require different kinds of interactions with the driver, making it difficult to develop a single standardized test until AV standards are in place.

Alternatively, policymakers may forgo practical testing of drivers or vehicles entirely. They may instead rely on manufacturers or third parties to ensure vehicle safety and to ensure that the driver has been properly trained in using the vehicle and understands its limitations. Policymakers may additionally require drivers and/or manufacturers to hold additional insurance to bear liability for crashes. These approaches may shield transportation agencies from costs and liability, but they will not necessarily lead to greater road safety. As we discuss in Chapter Three, different states are using different approaches to navigate these complex regulatory aims.

The diversity of vehicle capabilities, and of the ways in which vehicles may suffer failures, also suggest that safety and performance standards for AVs will be significantly different from those of traditional vehicles. Standards may specify capability requirements focused on sensing different objects in the environment under different conditions, system redundancy, graceful degradation, emergency behaviors, physical safety, and software and communication integrity. We discuss standards in Chapter Seven.

Finally, there are some opportunities for transportation agencies to take near-term actions to increase AV safety. Currently, while DOTs have codes for signage and markings, these are sometimes not conformed to in practice. This poses challenges for vehicle perception and navigation, particularly through construction areas or irregular routes. DOTs could require stricter conformance to road signage and marking standards to make the perception challenge easier. Standardization across states would also be significantly beneficial; not only for AV owners but also conventional drivers who sometimes struggle to understand confusing detour markings.

Similarly, transportation agencies could further maintain and provide online, real-time, detailed records of construction and other variations in the transportation system. Such information could leverage the record-keeping that transportation agencies already use, but would be more widespread than existing record systems, which focus on highways, and provide a higher level of detail. Such efforts would aid both AVs and human drivers who could use such up-to-date information for real-time route planning.

Conclusion

AVs have been an area of research for many decades. Efforts of the last 15 years, first by universities and then by industry, have brought this technology to near readiness. Deployment still faces several challenges, however. Perception of the environment remains the biggest challenge to reliable driving. New nondriving challenges have also emerged, such as ensuring system security and integrity.

In the near term, manufacturers are likely to develop vehicles with significantly different capabilities. These have a number of policy implications, including the challenge for policymakers to regulate many diverse vehicles with different operating constraints, and to ensure that drivers understand these vehicles' capabilities and can operate them safely.