American Journal of
Preventive Medicine

RESEARCH ARTICLE

Automated Vehicles and Pedestrian Safety: Exploring the Promise and Limits of Pedestrian Detection

Tabitha S. Combs, PhD,[1] Laura S. Sandt, PhD,[2] Michael P. Clamann, PhD,[2] Noreen C. McDonald, PhD[1]

Introduction: U.S. pedestrian fatalities have risen recently, even as vehicles are equipped with increasingly sophisticated safety and crash avoidance technology. Many experts expect that advances in automated vehicle technology will reduce pedestrian fatalities substantially through eliminating crashes caused by human error. This paper investigates automated vehicles' potential for reducing pedestrian fatalities by analyzing nearly 5,000 pedestrian fatalities recorded in 2015 in the Fatality Analysis Reporting System, virtually reconstructing them under a hypothetical scenario that replaces involved vehicles with automated versions equipped with state-of-the-art (as of December 2017) sensor technology.

Methods: This research involved the following activities: (1) establish functional ranges of state-of-the-art pedestrian sensor technologies, (2) use data from the Fatality Analysis Reporting System to identify pedestrian fatalities recorded in each state in the U.S. and District of Columbia in 2015, and (3) assess the maximum numbers of pedestrian fatalities that could have been avoided had involved vehicles been replaced with autonomous versions equipped with the described sensors. The research was conducted from July to December 2017.

Results: Sensors' abilities to detect pedestrians in advance of fatal collisions vary from <30% to >90% of fatalities. Combining sensor technologies offers the greatest potential for eliminating fatalities, but may be unrealistically expensive. Furthermore, whereas initial deployment of automated vehicles will likely be restricted to freeways and select urban areas, non-freeway streets and rural settings account for a substantial share of pedestrian fatalities.

Conclusions: Although technologies are being developed for automated vehicles to successfully detect pedestrians in advance of most fatal collisions, the current costs and operating conditions of those technologies substantially decrease the potential for automated vehicles to radically reduce pedestrian fatalities in the short term.

INTRODUCTION

Annual U.S. pedestrian fatalities increased more than 30% between 2009 and 2016; approximately 6,000 pedestrians were killed in 2016, the highest level in nearly 3 decades.[1,2] Many experts claim advances in vehicle automation will significantly address this public health crisis, citing the statistic that 94% of traffic fatalities are due to human error, and arguing that fully automated vehicles (AVs) will eliminate these error-caused fatalities.[3,4] This hope is an important part of the political discussion on AV regulation.[4]

From the [1]Department of City and Regional Planning, University of North Carolina, Chapel Hill, North Carolina; and [2]Highway Safety Research Center, University of North Carolina, Chapel Hill, North Carolina

Address correspondence to: Tabitha S. Combs, PhD, Department of City and Regional Planning, University of North Carolina, Campus Box 3140, New East Building, Chapel Hill NC 27599. E-mail: tacombs@live.unc.edu.

0749-3797/$36.00
https://doi.org/10.1016/j.amepre.2018.06.024

The foundation of AV technology is effective detection. Before vehicles can understand and respond to their surroundings, they must be able to detect important road elements, including pedestrians. AVs face substantial challenges in accurately and reliably detecting and recognizing pedestrians, who are more difficult to identify, predict, and protect in the event of a crash compared with other road users. Pedestrians have variable physical characteristics and appear in a variety of environments with different background features, obstacles, and weather conditions, making them difficult to see. Vehicle-based sensors can fail to identify pedestrians even in ideal conditions, and especially when those pedestrians are small, too far or too close to the vehicle, or partially occluded by nearby objects.[5] A 2017 study using the CalTech Pedestrian Detection Benchmark data (a 10-hour video recorded from a vehicle's perspective) suggests a tenfold improvement in this technology is needed to replicate human performance.[6,7]

This paper focuses on the first stage of detection: sensing (the second half of detection occurs when on-board computers process and interpret sensed images or signals). There is neither consensus among manufacturers as to which of the many available classes of sensors perform best nor any set standard for assessing sensor performance. Production AVs are likely to incorporate multisensor systems combining several overlapping technologies so the strengths of one sensor offset the weaknesses of another.[8,9]

The most common classes of sensors presently used in automated driving applications include visible-light cameras (VLC), light detection and ranging (LiDAR), and radar (although infrared imaging technology is commonly used in driver assistance systems, e.g., parking assist, it has not been widely deployed in AV applications).[10−12] Nearly all sensors are unique and proprietary, meaning their capabilities and limitations vary across applications. Within sensor classes, however, individual applications share some common limitations, described below.

Multiple VLCs capture images and send them to onboard computers, which compile and analyze them for pedestrians and objects. VLCs function poorly in low-light conditions, in adverse weather conditions, and on slick surfaces where glare might be a factor.[8,13]

LiDAR uses scanning lasers to measure distances to surfaces, producing a three-dimensional map of detailed shapes. LiDAR is capable of object detection in low/no-light conditions, but like VLC, is unreliable in adverse weather and when road surfaces are wet or reflective.[14] LiDAR is potentially useful for medium- and long-range detection, but is typically deployed as a single unit on a vehicle's rooftop, with its "view" of the ground surrounding the vehicle obstructed by the vehicle itself, hindering detection at very close range.[8,15,16]

Radar uses radio waves to detect objects and determine distances and relative speeds. Radar handles darkness and adverse weather conditions well, but has poor resolution, making it difficult to distinguish pedestrians, especially children.[17] Radar also cannot reliably detect stationary objects (such as pedestrians waiting to enter a roadway).[14,18,19]

The objective of the study is to estimate the maximum number of pedestrian fatalities that could have been avoided if the striking vehicles were replaced with fully automated versions equipped with ideal, state-of-the-art pedestrian sensors. This is done by cross-checking the conditions of each fatality with known functional limitations of each of the three sensor classes. The output of the analysis is a "potential effectiveness ratio" (PER): the estimated maximum number of theoretically preventable fatalities divided by total transportation-related pedestrian fatalities. PER has a theoretical range of 0 to 1, with 1 representing perfect performance.

METHODS

Study Population

The authors use 2015 data from the Fatality Analysis Reporting System (FARS) to identify all vehicular crashes resulting in at least one pedestrian fatality. FARS is administered by the National Highway Traffic Safety Administration and provides a census of fatalities resulting from motor vehicle crashes in all 50 states and Washington, DC.[20] The data include a range of detailed crash information, including time and location of the crash, weather conditions, roadway features, and pre-crash behaviors and impairment status of drivers and pedestrians. Appendix Table 1 (available online) provides information on FARS-derived variables used in this analysis. All analyses were conducted between July and December 2017.

The authors focus on the sensing stage of pedestrian detection, assuming by the time fully automated vehicles are on the road, their software will be nearly 100% effective at recognizing and predicting movements of pedestrians based on sensed images or signals. Although this is a strong assumption, software improvements have been rapid over the past decade and are likely to continue.[21] It is also assumed vehicles' crash-avoidance technologies are near perfect and, with few exceptions, a pedestrian detected is a fatality avoided. The models thus provide an idealized, maximum estimate of the ability of AVs to reduce pedestrian fatalities.

Measures

The first step of the analysis is identifying transportation-related fatalities that could have been avoided had all involved vehicles been equipped with state-of-the-art pedestrian detection systems and "ideal" crash-avoidance technology. Transportation-related fatalities include all pedestrian fatalities recorded in FARS, except those related to domestic disputes, involving disabled or unoccupied vehicles, or occurring because of “other unusual circumstances,” as well as fatalities not occurring as part of a crash’s “first harmful event.”

Next, transportation-related fatalities are classified into three groups: obsolete, unavoidable, and preventable. Obsolete fatalities arise from situations that are extremely unlikely to occur when vehicles are autonomously operated, presuming AVs are programmed to operate safely at all times. These include police pursuits; distracted, drowsy, or impaired drivers; and out-of-control vehicles.

Regardless of detection or automation technology, every vehicle has physical limits (e.g., stopping distance), rendering some crashes impossible to avoid. Slick or substandard road surfaces also interfere with the physical ability of many vehicles to avoid collision. Modeling the physical limits of striking vehicles is beyond the scope of this analysis. Instead, the authors take a best-case scenario approach, and assume only those fatalities resulting from pedestrians darting out from behind obstructions are unavoidable.

The remaining transportation-relevant fatalities are considered preventable (i.e., potentially avoidable given appropriate detection and automation technology). This approach assumes AVs are programmed to operate safely, at lawful and appropriate speeds given roadway conditions and pedestrian activity, and that pedestrian detection is the only barrier to elimination of pedestrian fatalities.

Finally, functional ranges are established for each sensor class based on known technological limitations. Because of the proprietary nature of this technology, manufacturers do not publish effectiveness estimates. Sensors are presumed to be 100% effective (f=1) at detecting pedestrians when all relevant crash characteristics fall within the functional range. Outside functional ranges, sensors are presumed to be ineffective, which is modeled both as complete failure to detect (f=0) and modest detection (f=0.2). The modest detection model is based on prior research, which found VLC applications were able to “see” pedestrians after nightfall in ≅20% of simulated cases[22]; this estimate is applied to all technologies, as other estimates are unavailable. When different sensor types are deployed in combination, effectiveness equals the maximum effectiveness of any sensor in the combination.

The following functional ranges are established for each of the technologies examined:

- VLC: ineffective from dusk to dawn, during adverse weather, and when crashes occur on reflective (i.e., wet) road surfaces; otherwise effective;
- LiDAR: ineffective during adverse weather, on reflective road surfaces, and when pedestrians first become visible at close range; otherwise effective; and
- Radar: ineffective when pedestrians are stationary before or at impact; otherwise effective.

Analysis

Each sensor technology’s (t) maximum overall potential effectiveness ratio (PER_t) is estimated as:

$$PER_t = \frac{b + \sum [n_c * (1 - f_{tc})]}{r}, \text{ with}$$

b = number of fatalities from obsolete crash types,
n_c = number of preventable fatalities occurring with crash characteristic c,
f_{tc} = effectiveness of sensor t with crash characteristic c, and
r = number of transportation-related fatalities.

PER is also calculated for different settings and victim characteristics (urban versus rural, crashes occurring on freeways versus other surface streets, crashes occurring at intersections or crosswalks versus other locations, and crashes involving fatalities of minors versus adults).

RESULTS

Of 5,261 pedestrian fatalities recorded in 2015, 337 were excluded because of missing data on variables used to determine applicability of sensor technologies. The authors also excluded as non-transportation-related 19 fatalities involving domestic disputes, 157 involving disabled or unoccupied vehicles, 51 because of other unusual circumstances, and 456 fatalities not occurring as part of a crash’s first harmful event, yielding a total of 4,241 transportation-related pedestrian fatalities. A further 792 fatalities were classified as obsolete, including 601 involving distracted, drowsy, or impaired drivers, 260 involving out of control vehicles, and 7 police pursuits (total obsolete-crash fatalities $<$ sum of obsolete fatality types due to overlap among criteria used to identify and classify obsolete crashes). Finally, 63 fatalities resulting from pedestrian dart-outs were classified as unavoidable. The authors classified the remaining 3,386 pedestrian fatalities as preventable.

The majority (77%) of preventable fatalities resulted from crashes occurring between dusk and dawn (Table 1). Across crash conditions, the share of fatalities occurring between dusk and dawn ranged from 56% (for minors) to 86% (along freeways). Adverse weather was characteristic of only 10% of fatalities, and 6% of minor-involved pedestrian fatalities. Similar figures are seen for reflective road surfaces. Close range was a factor in 5% to 12% of preventable crashes with one noteworthy exception: children. More than 25% of child fatalities occurred in close-range crashes. Stationary pedestrians generally accounted for a small ($<$10%) proportion of pedestrian fatalities.

Figure 1 shows PER and estimated pedestrian fatalities eliminated by each sensor class, given limitations based on crash characteristics (out-of-range crashes modeled at f=0). The results show a wide range in sensors’ potential effectiveness. The authors stress these results are estimates, based on assumptions regarding the capabilities of various sensors and algorithms governing the behavior of hypothetical AVs on which the sensors might be installed, as well as the physical limitations of those vehicles. It is also assumed neither the behaviors of pedestrians nor human drivers evolve to adapt to an AV-dominant transportation system, and that policies, road use norms, and infrastructure likewise do not adapt to the presence of AVs.

Given the characteristics of pedestrian fatalities presented above, it is not surprising to see VLC perform poorly, with an overall PER_{VLC} of 0.36. This finding is consistent with a 2011 effort to identify the limits of camera-based detection systems.[23] PER_{VLC} ranges from 0.22 for freeway conditions to 0.51 for fatalities involving minors, who are less likely than adults to be traveling on foot after dusk. LiDAR and VLC+LiDAR appear to perform substantially better than VLC alone, with overall and condition-specific $PER_{VLC+LiDAR}$ falling almost entirely between 0.70 and 0.86. The authors note that VLC+LiDAR provides a small improvement over LiDAR alone in all conditions except when victims are minors. Complementing LiDAR with VLC yields a substantial improvement (≅25%) in fatality avoidance among minors, compared with equipping vehicles with LiDAR alone. Adding radar to the sensor package results in further improvements in the potential reduction of pedestrian fatalities, with $PER_{VLC+LiDAR+radar} > 0.90$ across crash conditions.

When out-of-range effectiveness is modeled at 0.2, there are modest improvements. PER_{VLC} increases from 0.36 to 0.48, but is still substantially below the effectiveness of the other sensor types. PER_{LiDAR} increases from 0.80 to 0.83; PER_{radar} remains virtually unchanged at 0.95. PER for sensor combinations shows similarly small improvements at $f = 0.2$.

DISCUSSION

The authors find that current state-of-the-art detection technologies vary widely in their potential to detect and avoid fatal collisions with pedestrians, from less than 30% (VLC alone) to over 90% (VLC+LiDAR+radar) of preventable fatalities. Although none of the technologies alone yields the substantial decreases in pedestrian fatalities AV advocates expect, they do each appear to promise non-negligible improvements in pedestrian safety over conventional vehicles (e.g., VLC alone theoretically would have been able to detect—and potentially avoid—at least 700 pedestrian fatalities in 2015).

Radar displayed the highest independent PER, but its inability to recognize small or stationary pedestrians is a fundamental technological barrier. Between VLC and LiDAR, LiDAR appears to be the clear leader, given its ability to function in the dark, when roughly three quarters of pedestrian fatalities occur. However, state-of-the-art LiDAR sensors are currently cost prohibitive (though expected to drop), adding up to $85,000 to a vehicle's purchase price.[24]

The authors acknowledge the generosity of the assumptions for this simulation, including vehicles that are fully—and perfectly—automated, and adhere strictly to traffic norms and laws. Yet one of the biggest assumptions embedded in these results is the presumption that vehicles will operate in all parts of the U.S. This may not be the case, at least for several decades. In the near term, most major manufacturers plan to limit fully automated use of their vehicles to areas that fall within their operational design domains, which are largely restricted to freeways and well-mapped urban areas, where infrastructure can be carefully monitored and maintained, and where "smart" intersections and crosswalks may be able to relay information on pedestrian activity to AVs.[25−29] However, these settings are not where the majority of pedestrian fatalities take place: 20% (*n*=860) of transport-related pedestrian fatalities in 2015 occurred in rural areas, 79% (*n*=3,362) on non-freeway streets, and 87% (*n*=3,694) in locations other than intersections and crosswalks.[20] Until AVs are capable of operating safely in fully automated mode in these

Table 1. Proportion of Preventable Fatalities Meeting Relevant Crash Characteristics, Overall and by Crash Condition

Crash condition	Dusk to dawn	Adverse weather	Reflective surfaces	Close range	Stationary pedestrians	Preventable fatalities, *n*
Overall	0.77	0.10	0.14	0.11	0.05	3,386
Urbanicity						
Rural	0.82	0.10	0.13	0.10	0.09	681
Urban	0.75	0.11	0.14	0.11	0.04	2,382
Intersection/crosswalk						
Not intersection/crosswalk	0.81	0.11	0.13	0.11	0.06	2,713
Intersection/crosswalk	0.61	0.09	0.15	0.08	0.01	673
Freeway/highway						
Not freeway/highway	0.75	0.11	0.14	0.12	0.05	2,904
Freeway/highway	0.86	0.07	0.11	0.05	0.05	482
Age						
Minor	0.56	0.06	0.09	0.27	0.04	232
Adult	0.78	0.11	0.14	0.10	0.05	3,154

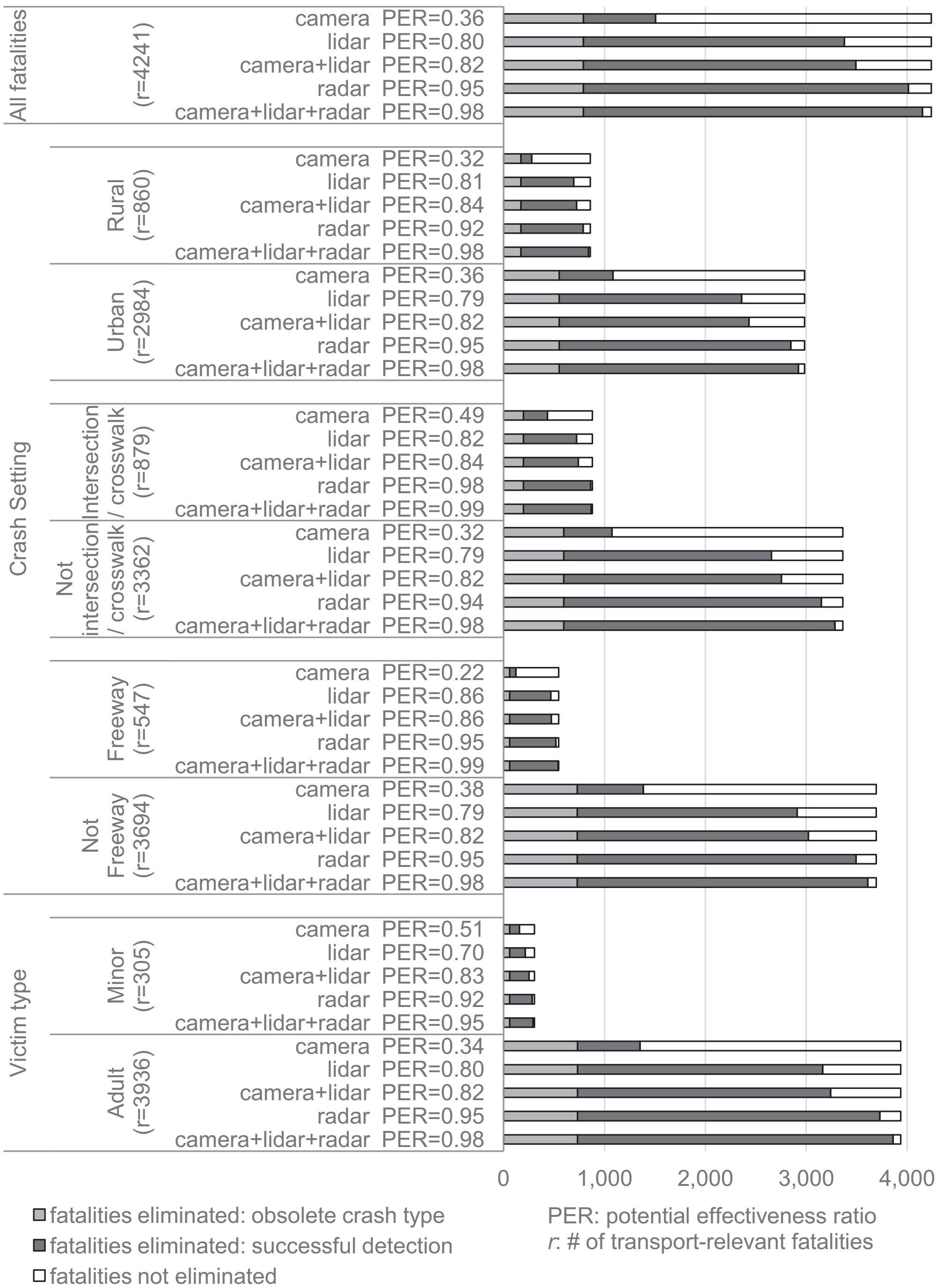

Figure 1. Pedestrian fatalities eliminated based on sensor technology and conditions.

settings—and until they are commonplace in these settings—they will provide only minimal improvements in the overall loss of pedestrian life.

Limitations

It is important to highlight areas that the authors did not investigate or were forced to make limited assumptions. Physical limits on vehicle performance are not critically addressed. Detailed data on sensor capabilities under varying conditions are not available in the literature. The algorithms governing how vehicles respond to information from sensors, assess and weigh crash risks, and execute appropriate avoidance behaviors post-detection are assumed to function flawlessly (the efficacy of various algorithms governing AVs' pre-detection operations has been examined elsewhere).[30] Finally, it is assumed that in every crash there is at least one way to avoid loss of pedestrian life without incurring loss of other lives. These are large assumptions, and are the topic of rich academic, philosophical, and technological debate.[31−33] But until developers and manufacturers reach consensus on standards for testing and independently verifying claims regarding the performance of their detection technology, researchers—and more importantly, policymakers—are left making educated guesses about what sorts of improvements in safety the public can actually expect from these technologies.

Also, the technologies likely have limitations that the authors were unable to capture using the crash characteristics provided in the FARS data. For example, cameras are known to struggle to pick out pedestrians on "busy" backgrounds, and when vehicles are traveling at high speeds.[23] LiDAR struggles to recognize non-grounded objects: a LiDAR-equipped AV prototype was reported to have repeatedly failed to detect kangaroos on Australian roads, raising questions about whether LiDAR would also fail to recognize humans moving in unexpected ways (e.g., skipping, hopping).[34]

Additionally, there are other promising technologies intended to protect pedestrians that the authors did not model, including navigation systems that direct motorized traffic away from crowded pedestrian areas, and vehicle-to-person beacons and smartphone apps to alert drivers and pedestrians of each other's presence.

Finally, the *ceteris paribus* assumption that neither pedestrians nor human drivers, infrastructure, policies, or enforcement norms will evolve as the motor vehicle fleet becomes more automated is clearly invalid. Human behavior will almost certainly adapt to the presence of AVs as humans learn what normative AV behaviors are and respond accordingly.[35]

CONCLUSIONS

This paper shows that deployment of multiple, state-of-the art pedestrian detection technologies on AVs could greatly reduce pedestrian fatalities in the U.S. However, this hopeful message is tempered by critical realities. First, the most affordable detection technology, cameras, is unlikely to be effective in pedestrian fatality mitigation. The most promising path to detecting pedestrians and avoiding pedestrian fatalities is via more expensive combinations of cameras, LiDAR, and radar-based detection systems. Second, the likely geography of AV deployment and the geography of pedestrian fatalities are not well matched, with the bulk of fatalities occurring on non-freeway streets away from intersections and crosswalks, where AV operations may be limited in the near future.

These findings underscore the need to continue thinking about complementary solutions, including technological advances, such as improved lighting and "smart" infrastructure, and development of a safe systems approach to transportation policy and roadway design. For example, policies could establish pedestrian priority zones, promote neighborhood designs that encourage walking in residential and commercial areas, and restrict vehicle speeds in those areas. Indeed, at least one recent study presents evidence that complementary solutions aimed at increasing walkability and interaction among modes of transportation may actually have a substantially greater positive impact on pedestrian safety than would efforts to eliminate driver error through automation.[36] Systems-oriented solutions are also important because they may address certain types of fatal pedestrian crashes, such as dart-outs and other physically unavoidable crashes, that improved vehicle detection alone will be unable to address.

As policymakers continue to enact legislation and consider the benefits and repercussions of automated driving, it will be critical to have better data and methods to independently assess technologies, to be able to more realistically estimate the likely safety benefits, and to consider for whom and where these benefits may accrue.[37] Pedestrians in particular merit more thorough consideration of the impacts that vehicle automation will have, not just with respect to crash avoidance, but also accessibility, comfort, and mobility, to ensure that the needs of the most vulnerable, yet most essential travel mode, are protected.

ACKNOWLEDGMENTS

This research was made possible with funding from the Collaborative Sciences Center for Road Safety, which operates under U.S. Department of Transportation Grant 69A3551747113.

This work was completed while Michael P. Clamann was at the Pratt School of Engineering, Duke University, Durham, North Carolina.

No financial disclosures were reported by the authors of this paper.

SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2018.06.024.

REFERENCES

1. Chang D. National pedestrian crash report. National Center for Statistics. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/810968. Published 2008. Accessed June 20, 2017.
2. Yanagisawa M, Swanson E, Najm WG. Target crashes and safety benefits estimation methodology for pedestrian crash avoidance/mitigation systems. National Highway Traffic Safety Administration. https://trid.trb.org/view.aspx?id = 1314139. Published 2014. Accessed June 7, 2017.

3. McCauley R. Congress releases guidelines in effort to regulate autonomous vehicles. GovTech.com. www.govtech.com/fs/Congress-Releases-Guidelines-in-Effort-to-Regulate-Autonomous-Vehicles.html. Published June 15, 2017. Accessed July 13, 2017.
4. Thune J, Bainwol M, Csongor R, Maddox JM, Sheehey-Church C. Paving the way for self-driving vehicles. www.commerce.senate.gov/public/index.cfm/2017/6/paving-the-way-for-self-driving-vehicles. Published 2017. Accessed July 13, 2017.
5. Dollar P, Wojek C, Schiele B, Perona P. Pedestrian detection: an evaluation of the state of the art. *IEEE Trans Pattern Anal Mach Intell.* 2012;34(4):743–761. https://doi.org/10.1109/TPAMI.2011.155.
6. Zhang S, Benenson R, Omran M, Hosang J, Schiele B. Towards reaching human performance in pedestrian detection. *IEEE Trans Pattern Anal Mach Intell.* 2018;40(4):973–986. https://doi.org/10.1109/TPAMI.2017.2700460.
7. Caltech Pedestrian Detection Benchmark. www.vision.caltech.edu/Image_Datasets/CaltechPedestrians/. Published December 12, 2016. Accessed July 31 2017.
8. Barnard M. Tesla & Google disagree about LIDAR—which is right? CleanTechnica. https://cleantechnica.com/2016/07/29/tesla-google-disagree-lidar-right/. Published July 29, 2016. Accessed July 26, 2017.
9. Santo D. Autonomous cars' pick: camera, radar, Lidar? EE Times. www.eetimes.com/author.asp?section_id = 36&doc_id = 1330069. Published July 7, 2016. Accessed July 31, 2017.
10. Condliffe J. Thermal imaging aims to give autonomous cars better night vision. *MIT Technol Rev.* www.technologyreview.com/the-download/608838/thermal-imaging-aims-to-give-autonomous-cars-better-night-vision/. Published September 12, 2017. Accessed May 24, 2018.
11. Baldwin R. Thermal cameras could be key to safer self-driving vehicles. *Engadget.* www.engadget.com/2018/02/14/adasky-thermal-camera/. Published February 14, 2018. Accessed May 24, 2018.
12. Davies A. Heat-seeking cameras could help keep self-driving cars safe. *WIRED.* www.wired.com/story/self-driving-cars-thermal-image-cameras/. Published April 21, 2018. Accessed May 24, 2018.
13. Sandt L, Owens JM. *A Discussion Guide for Automated and Connected Vehicles, Pedestrians, and Bicyclists.* Chapel Hill, NC: Pedestrian and Bicycle Information Center, 2017.
14. Turnbull KF, Cherrington L, Elgart Z, et al. *Automated and Connected Vehicle (AC/CV) Test Bed to Improve Transit, Bicycle, and Pedestrian Safety: Technical Report.* College Station, TX: Texas A&M Transportation Institute; 2017: 132. https://ntl.bts.gov/lib/61000/61800/61889/0-6875-1.pdf. Accessed June 13, 2017.
15. Velodyne. Users Manual and Program Guide, HDL-64E S3. 2017. http://velodynelidar.com/docs/manuals/63-HDL64ES3%20REV%20J%20MANUAL,USERS%20AND%20PROGRAM%20GUIDE,HDL-64E%20S3.pdf. Published 2017. Accessed July 30 2017.
16. Simonite T. Self-driving cars rely on sensor technology not ready for the mass market. *MIT Technol Rev.* www.technologyreview.com/s/603885/autonomous-cars-lidar-sensors/. Published March 20, 2017. Accessed July 27, 2017.
17. Ryde J, Hillier N. Performance of laser and radar ranging devices in adverse environmental conditions. *J Field Robot.* 2009;26(9):712–727. https://doi.org/10.1002/rob.20310.
18. Manston K. The challenges of using radar for pedestrian detection. In: The 16th JCT Traffic Signal Symposium. Warwick, UK; 2011. http://jctconsultancy.co.uk/Symposium/Symposium2011/PapersForDownload/The%20challenges%20of%20using%20radar%20for%20pedestrian%20detection%20Keith%20Manston%20Siemens.pdf. Accessed July 24, 2017
19. Bartsch A, Fitzek F, Rasshofer RH. Pedestrian recognition using automotive radar sensors. *Adv Radio Sci.* 2012;10:45–55. https://doi.org/10.5194/ars-10-45-2012.
20. National Highway Traffic Safety Administration. Fatality Analysis Reporting System (FARS). National Highway Traffic Safety Administration; 2016. www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars. Published November 14, 2016. Accessed July 31, 2017.
21. Benenson R, Omran M, Hosang J, Schiele B. Ten years of pedestrian detection, what have we learned? In: Agapito L, Bronstein MM, Rother C, eds. *Computer Vision - ECCV 2014 Workshops. Lecture Notes in Computer Science.* New York: Springer International Publishing; 2015:613–627.
22. González A, Fang Z, Socarras Y, et al. Pedestrian detection at day/night time with visible and FIR cameras: a comparison. *Sensors.* 2016;16(6):820. https://doi.org/10.3390/s16060820.
23. Jermakian JS, Zuby DS. *Primary Pedestrian Crash Scenarios: Factors Relevant to the Design of Pedestrian Detection Systems.* Arlington, VA: Insurance Institute for Highway Safety. www.iihs.org/frontend/iihs/documents/masterfiledocs.ashx?id = 1888. Published 2011. Accessed April 17, 2018.
24. LeVine S, LeVine S. What it really costs to turn a car into a self-driving vehicle. *Quartz.* https://qz.com/924212/what-it-really-costs-to-turn-a-car-into-a-self-driving-vehicle/. Published March 2017. Accessed July 31, 2017.
25. Byford S. Honda reveals its plans for autonomous vehicles. *The Verge.* www.theverge.com/2017/6/8/15761272/honda-self-driving-cars-autonomous-level-4-date. Published June 8, 2017. Accessed December 11, 2017.
26. Crosbie J. Ford's self-driving cars will live inside urban "geofences.". *Inverse.* www.inverse.com/article/28876-ford-self-driving-cars-geofences-ride-sharing. Published March 13, 2017. Accessed December 11, 2017.
27. Waymo. Waymo Safety Report: on the road to fully self-driving. https://storage.googleapis.com/sdc-prod/v1/safety-report/waymo-safety-report-2017.pdf. Published 2017. Accessed March 30, 2018.
28. General Motors. 2018 Self-Driving Safety Report. www.gm.com/content/dam/gm/en_us/english/selfdriving/gmsafetyreport.pdf. Published 2018. Accessed March 30, 2018.
29. Foss K. Welcome to your autonomous life: self driving cars are a new reality. *Sci Trends.* https://sciencetrends.com/welcome-autonomous-life-self-driving-cars-new-reality/. Published August 2017. Accessed March 30, 2018.
30. Detwiller M, Gabler HC. Potential reduction in pedestrian collisions with an autonomous vehicle. Paper presented at: 25th International Technical Conference on the Enhanced Safety of Vehicles (ESV) National Highway Traffic Safety Administration. https://www-esv.nhtsa.dot.gov/Proceedings/25/25ESV-000404.pdf. Published 2017. Accessed September 1, 2018
31. Noothigattu R, Gaikwad NSS, Awad E, et al. A voting-based system for ethical decision making. ArXiv170906692 Cs. http://arxiv.org/abs/1709.06692. Published September 2017. Accessed April 16, 2018.
32. Bonnefon J-F, Shariff A, Rahwan I. The social dilemma of autonomous vehicles. *Science.* 2016;352(6293):1573–1576. https://doi.org/10.1126/science.aaf2654.
33. Shariff A, Bonnefon J-F, Rahwan I. Psychological roadblocks to the adoption of self-driving vehicles. *Nat Hum Behav.* 2017;1(10):694–696. https://doi.org/10.1038/s41562-017-0202-6.
34. Deahl D. Volvo's self-driving cars are having trouble recognizing kangaroos. *The Verge.* www.theverge.com/2017/7/3/15916076/volvo-self-driving-cars-trouble-recognizing-kangaroos. Published July 3, 2017. Accessed July 31, 2017.
35. Millard-Ball A. Pedestrians, autonomous vehicles, and cities. *J Plan Educ Res.* 2018;38(1):6–12. https://doi.org/10.1177/0739456X16675674.
36. Dumbaugh E, Li W. Designing for the safety of pedestrians, cyclists, and motorists in urban environments. *J Am Plann Assoc.* 2010;77(1):69–88. https://doi.org/10.1080/01944363.2011.536101.
37. Shepardson D. UPDATE 1-U.S. House panel approves legislation to speed deployment of self-driving cars. Reuters; www.reuters.com/article/usa-selfdriving-vehicles-idUSL1N1KI1ES. Published July 27, 2017. Accessed July 31, 2017.