BIG DATA IN TESLA VEHICLES AND THE INTERNET OF VEHICLES(IOV)

Submitted by: Karan Ajay Pisay

University of Maryland, Baltimore County

DATA 603: Platforms for Big Data Processing

Prof. Donghwa Kim

05/24/2022

Abstract:

The possibility of highly automated vehicles on every route appears to be growing. The demand for self-driving car research has never been higher, with businesses like Tesla, Google, BMW, and others vying to develop a completely autonomous vehicle. Modern automobiles are expected to be connected through heterogeneous radio access technologies and be able to share huge amounts of data with their surroundings due to the rapid growth of automotive telematics. Traditional Vehicular Ad-Hoc Networks (VANETs) are developing to the Internet of Vehicles (IoV), which offers an efficient and intelligent future transportation system by dramatically expanding network scale and conducting both real-time and long-term information processing. Automated vehicles, on the other hand, not only consume but also generate large amounts of data known as big data. Furthermore, this data is generated processed, and stored for its future use.

Introduction:

Many countries' transportation networks are currently being pushed to their limits as the number of people using them continues to rise. These transportation systems have grown inefficient and expensive to maintain or modernize in many cases. According to a recent report, the number of cars in use worldwide (including passenger and commercial) is slightly greater than one billion and is predicted to reach two billion by 2035. The rapid increase in the number of automobiles leads to increased traffic congestion and the number of fatalities caused by road accidents. We expect significant changes in the transportation system in the future to meet the needs of new cars, passengers, and drivers, as well as new paradigms like the Internet of Things (IoT) and cloud computing. Recent advancements in computing and networking technology have resulted in the creation of a diverse spectrum of intelligent gadgets, many of which are equipped with embedded processors and wireless communication technologies. Through their interconnection and interoperability, these intelligent gadgets are being deployed to provide a safer and more convenient environment, resulting in the new notion of IoT (An Overview of Internet of Vehicles, 2014).

Cars are no longer just simple vehicles, due to advancements in communication technology, mobile networks, and the automotive sector. Vehicles with smart equipment, such as wireless sensors, onboard computers, GPS transmitters, cameras, and other sensors, can collect and analyze massive volumes of data while also allowing for information exchange between vehicles. Automobile development is transitioning from a period of delivering traditional transportation services to a period of intelligent transportation (Survey on the Internet of Vehicles: Network Architectures and Applications, 2020).

With the advancement of self-driving car technology and testing, the possibility of privately owned self-driving cars operating on public highways is becoming a reality. By 2035, according to Navigant Research, 94.7 million vehicles with self-driving capability will be marketed yearly. Autonomous vehicles are vehicles that employ technology to replace a human driver partially or completely in moving a machine from point A to point B while collecting the environment, road, and traffic data and adapting to circumstances. Moreover, the utilization of sensors in autonomous vehicles is facilitated by big data. An autonomous vehicle will be useless on the road if it does not have access to a consistent and dependable stream of self-driving car big data (Internet of Vehicles in Big Data Era, 2018).

Literature Survey:

Many polls have been performed in the past to gauge public opinion on autonomous vehicles. People are drawn to self-driving cars because of their safety and convenience, but they are apprehensive about the lack of control, liability, and expense, according to previous research. Although most people embrace autonomous automobiles on principle, attitudes are divided. According to a recent poll, most individuals were optimistic about driverless automobiles but were concerned about security and legal difficulties. Another study indicated that most individuals were optimistic about driverless vehicles while also voicing safety concerns. However, one flaw in this research is that they were unable to examine the perspectives of people who had firsthand experience with autonomous vehicles (Morando et al., 2021).

Larsson observed in one research of real-world autonomous car use that adaptive cruise control (ACC) users encounter regular system limits and that the more they drive with ACC, the more they become aware of the system constraints. The same survey found that drivers make mode errors, leading to the conclusion that imperfect ACC is better for driving safety because it keeps drivers informed (Larsson, 2012) (Chen & Tomblin, 2021).

Our study expands on these findings by examining user experiences with the next generation of autonomous driving capabilities that combine ACC and steering assistance. We wanted to know how frequently drivers utilize these capabilities, how frequently they encounter errors, and how their opinions toward automation are influenced by their experiences with automation failures.

Big data gathering for autonomous vehicles and internet of vehicles:

As mentioned above, autonomous vehicles operate without human interference and are solely based on the sensors present on the vehicle to track its surrounding. The data is fed to the computer present in the car which then processes the car and operates itself. Sensors are required to collect data for autonomous vehicles, just as huge data is required for autonomous vehicles. Information from numerous built-in sensors is collected and analyzed in milliseconds in an autonomous vehicle. This enables the car to not only go safely from point A to point B, but also to send information about road conditions to the cloud and, as a result, to other vehicles. The information gathered by self-driving automobiles is subsequently shared with other vehicles. Moreover, an autonomous car uses three types of sensors to view and detect everything around it: camera, radar, and lidar (Fényes et al., 2019).

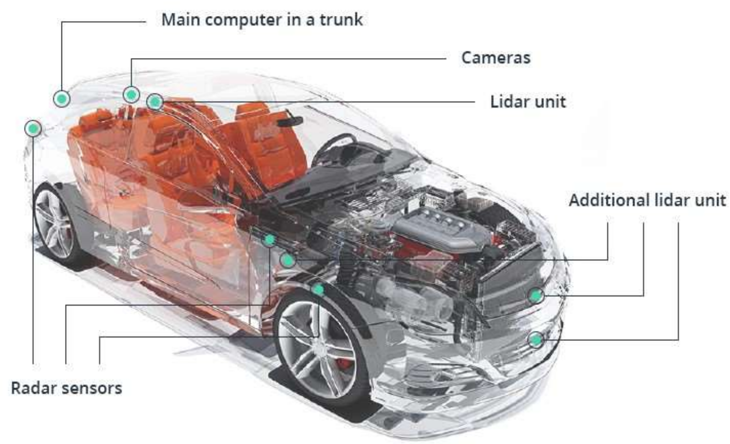

Fig01: Placement of sensors on a vehicle.

A vehicle's cameras allow it to acquire a 360-degree view of its surroundings. Modern cameras can also create a realistic 3D image, distinguish objects and people, and calculate their distance. The issue is that bad weather, damaged signs, and insufficient contrast put the camera's skills to the test. Other sensors, fortunately, can assist (Sensors and Sensor Fusion in Autonomous Vehicles, 2018).

Short-range and long-range radar is unaffected by weather conditions. Short-range waves aid with lane-keeping and parking by removing blind spots. Long-range radar can help in braking by measuring the distance between the car and other moving vehicles. To summarize, radar is used to detect moving objects while simultaneously measuring distance and speed (Sensors and Sensor Fusion in Autonomous Vehicles, 2018).

Lidar employs a laser instead of radio waves to create 3D images of the environment and map them, giving the driver a 360-degree perspective. Software that aids in the analysis of huge data in self-driving automobiles is another important component of autonomous driving. Smart cars, under their network connectivity, not only send data from all of their sensors to the cloud but also respond to changing conditions almost instantly. Some businesses collect and distribute big data to Tier 1 and Tier 2 vendors in the automotive sector. This information comprises unique scenarios, movies, and photos that help self-driving cars learn and develop a solid foundation for making decisions on the road (Sensors and Sensor Fusion in Autonomous Vehicles, 2018).

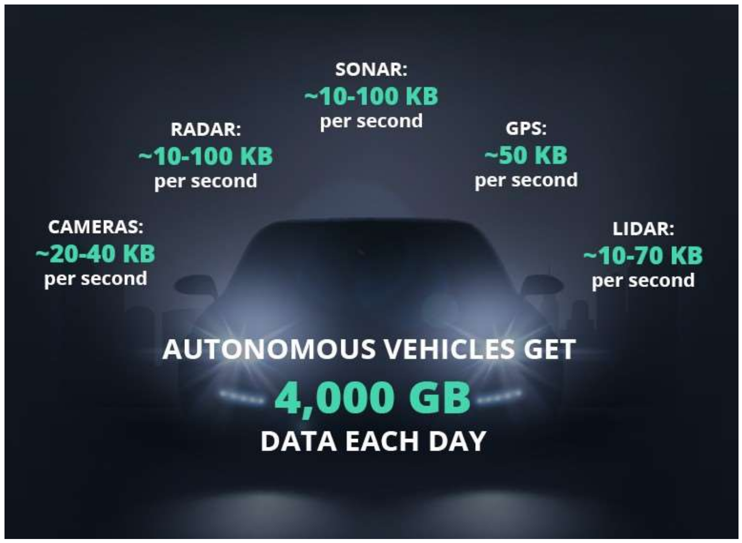

Fig: Amount of data generated by an automobile back to the servers.

Apart from the data processed by your car to drive you form point A to point B, your car also collects data to send it back to the sever which is processed and stored to generate insights about the driving patterns of the population. For example, as we are all aware of the autonomous vehicles manufactured by Tesla. So, Tesla is not a car manufacturing company, it is a company that collects big data from the cars they have manufactured. The information is used to create maps that show everything from the average increase in traffic speed along a stretch of road to the location of dangers that lead drivers to react. Machine learning in the cloud is in charge of educating the entire fleet, while edge computing determines what action the automobile should take right now. There is also a third level of decision-making, with cars being able to build networks with other Tesla vehicles nearby to share local information and insights. These networks will most likely interact with automobiles from other manufacturers as well as other systems such as traffic cameras, road-based sensors, or cellphones in a near future scenario when autonomous cars are widely used (Baucells & Yemen, 2019).

Fig: Road mapping at the backend severs (Baucells & Yemen, 2019).

Working of big data analysis

Tesla sensor data from its vehicles enabled it to create a map that is 10 times more precise than those supplied by competitors. It also uses a lot of this information to train its self-driving system, which adds a lot of value to both the vehicle and the brand. Sensors on both the inside and exterior of the automobiles feed the company's machine learning algorithms. They recognize various types of cars, driver attention, pedestrians, traffic signals, and so on, and make split-second judgments such as altering the vehicle's speed and heading. It's worth noting that Tesla develops most of its models in the cloud, and the vehicles only make judgments based on those models. This allows each vehicle to effectively have fleet information (Endsley, 2017).

Neural Networks: Train deep neural networks on challenges ranging from perception to control using cutting-edge research. To perform semantic segmentation, object detection, and monocular depth estimation, the per-camera networks evaluate raw images. The birds-eye-view networks use video from all cameras to produce a top-down image of the road layout, static infrastructure, and 3D objects. These networks learn from the world's most complex and diverse scenarios, which are iteratively sourced in real-time from our fleet of roughly 1 million vehicles. Autopilot neural networks require 48 networks to complete and 70,000 GPU hours to train. At each timestep, they generate 1,000 different predictions (Endsley, 2017).

Autonomy Algorithms: Create a high-fidelity picture of the world and design trajectories in that space to develop the key algorithms that operate the car. To train neural networks to predict such representations, combine information from the car's sensors across place and time to provide accurate and large-scale ground truth data. Build a comprehensive planning and decision-making system that can work in complex real-world circumstances under uncertainty using cutting-edge methodologies. Evaluate the algorithms using the Tesla fleet (Endsley, 2017).

Evaluation Infrastructure: To speed the pace of innovation, measure performance improvements, and avoid regressions, build open- and closed-loop, hardware-in-the-loop assessment tools and infrastructure at scale. Utilize our fleet's anonymized characteristic clips and incorporate them into a huge number of test scenarios. Write code that simulates our real-world environment, resulting in highly realistic visuals and other sensor data that is fed into our Autopilot software for live debugging and automated testing (Sadasivam, 2015).

How do autonomous vehicles operate using the data collected?

Let's consider the Tesla Model 3 for the analysis of how the autopilot works:

i. Sensors: Tesla obtains its data. It gets it from roughly two million vehicles with autopilot and uses it to train neural networks to detect objects, segment photos, and measure depth in real-time. For data collection, they placed an array of eight cameras. The deep neural networks are then operated using the onboard supercomputer, the FSD processor. They use real-time computer vision inputs from the cameras to comprehend, make decisions, and maneuver the car through the environment. Moreover, this also includes Autopilot capabilities, which let your vehicle drive, accelerate, and brake for you in practically any lane. On most highways, it will also change lanes automatically to pass other vehicles or navigate to interchanges and exits (Morando et al., 2021b).

   The sensors allow the car to detect when something is approaching too closely and determine the appropriate distance so that it can safely change lanes. It should be noted, however, that material covering these sensors can cause them to malfunction. The top windshield houses the forward-facing camera. A microprocessor inside the camera assists the car in determining what obstacles lie ahead. The camera serves as the eyes of the system. It allows the vehicle to detect traffic, pedestrians, road signs, lane markers, and anything else in front of it. This data is then used to assist the car is driving itself. When Autopilot is turned on, the car may drive within a lane, change lanes, manage the vehicle's speed, and regulate braking when traveling on the highway (Morando et al., 2021b).

ii. Planning: By drawing correlations between past and future, a neural network learns to predict the behavior of other road users. By drawing correlations between what it sees (through computer vision neural networks) and the actions made by human drivers, a neural network can learn to predict what a human driver would do. AlphaStar is possibly the biggest triumph of imitation learning to date. DeepMind trained a neural network to play like a person using samples from a database of millions of human-played StarCraft games. The network learned the relationships between game state and human player actions, allowing it to predict what a human would do in a given situation. AlphaStar achieved a level of ability that DeepMind estimates would place it about in the center of StarCraft's competitive rankings using only this training (Collingwood, 2018).

iii. Control: Tesla is using imitation learning to help with driving duties like handling the steep curves of a freeway cloverleaf or turning left at a junction. Once the data is submitted, no human labeling is required, just like with prediction. Because the neural network is predicting what a human driver would do in a given world state, it only needs the world state and the actions of the driver. Imitation learning is essentially anticipating the behavior of Tesla drivers rather than the behavior of other road users that Tesla observes. As with AlphaStar, the replay of what transpired has all of the necessary information. Furthermore, Sudden braking or swerving, automatic emergency braking, collisions or collision alerts, and more sophisticated machine learning approaches such as anomaly detection and novelty detection are all ways to collect intriguing replays. When the visual neural networks perceive a traffic light and the left turn signal is engaged, or the steering wheel turns left, Tesla can set up a trigger to collect a replay (Collingwood, 2018)

But, like any other system, it isn't perfect. It also necessitates constant human attention (Piesnack et al., 2013).

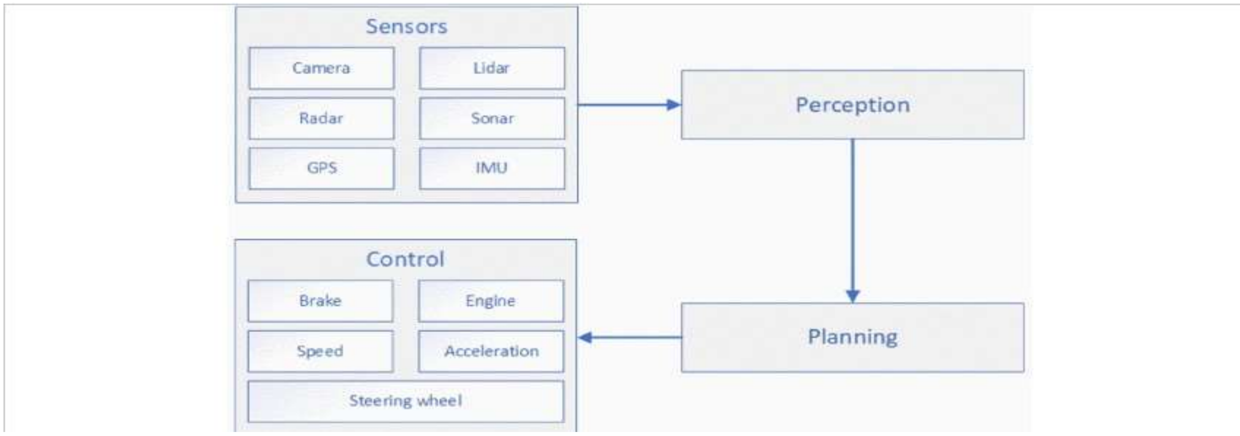

Fig: Block diagram of how autonomous vehicle operate

The lateral control design of the autonomous vehicle for path tracking is presented in this section. During the design process, the MPC structure is utilized, which incorporates the decision tree's outcome via constraints. The developed controller must be able to adjust to changing parameters like adhesion coefficient and longitudinal velocity (Fényes et al., 2021). The control design is based on the vehicle's lateral dynamics, which are composed of three equations:

- $\mathbf{mvx(\dot{\psi} + \dot{\beta}) = C1\alpha1 + C2\alpha2}$
- $\mathbf{J\ddot{\psi} = C1\alpha1l1 - C2\alpha2l2}$
- $\mathbf{\dot{v}y = vx(\dot{\psi} + \dot{\beta})}$

where J is the yaw inertia, m is the vehicle mass, Ci is the front and rear axle cornering stiffness, li is the distance between the vehicle center of gravity and the wheels, and 1 = l 1/vx and 2 = +l 2/vx are the tire side-slip angles. The vehicle's lateral velocity is vy, from which the lateral displacement y can be calculated. The equations can be converted to a state space representation with the state vector x = [v y y]T and the state-space representation x = Ax + Bu, where u is the steering angle (Fényes et al., 2021) (Pek & Althoff, 2021).

Utilization of Big Data in Tesla Vehicles

Big data assists Tesla in lowering costs, identifying market opportunities, ensuring customer satisfaction, developing new goods, and improving its vehicles. Moreover, hundreds of sensors and smart technology are built into the new generation of autonomous self-driving automobiles, whether electric or not. These smart automobiles can communicate with infrastructure and other smart cars thanks to recent improvements in the internet of things, smart cities, and wireless communication. The amount of data collected and transmitted will increase as autonomous linked vehicles and their interactions with smart cities become more common. Drivers also have a variety of sensors on their smartphones and wearable gadgets (Qian et al., 2019).

With internal and external sensors that may pick up information about a driver's hand placement on the gauges and how they are working them, Tesla effectively crowdsources its data from all its vehicles as well as their drivers. Tesla is responsible for the entire process of designing, developing, manufacturing, and marketing its electric vehicles. Tesla produces energy storage technologies in addition to automobiles. Tesla is divided into two operational segments: automotive and energy generation and storage. Designing, production, installation, and sales/lease of energy storage items and solar energy services to various residential and commercial customers are all included in the energy generation and storage section. Tesla is frequently referred to as a leader in artificial intelligence and big data analytics (Qian et al., 2019). Tesla automobiles are equipped with auto-pilot software. Tesla automobiles' auto-pilot software is updated remotely whenever new upgrades become available, making them more efficient. A neural net for vision, sonar, and radar processing is operated on Tesla's onboard computer. Tesla has also implemented fleet learning to help with analytics. Tesla's autopilot is also trained with acquired real-world data using deep neural network methods (Qian et al., 2019).

Autopilot Failures and recommendations:

The ability of a human driver to exert control is often used in car safety justifications for low-integrity technologies. If a software defect generates a potentially dangerous scenario with an Advanced Driver Assistance System (ADAS), for example, the driver may be asked to override that software function and return to a safe condition. Drivers should also be able to recover from major vehicle technical problems like tire blowouts. In other words, the driver of a human-driven vehicle is accountable for taking the appropriate corrective action. Controllability is defined as a situation in which the driver is unable to take remedial action and must be designed to a higher Automotive Safety Integrity Level, or ASIL. The driver of a completely autonomous car cannot be relied upon to manage unusual situations. Instead, the computer system must act as the primary exception handler for defects, malfunctions, and operational situations that are not stated. In comparison to ADAS systems, putting the computer in control of exception handling appears to drastically increase automation complexity. Lane-keeping and adaptive cruise control are two ADAS technologies that look tantalizingly close to fully autonomous operation. However, because there is no driver to grasp the wheel and press the brakes when something goes wrong, a completely autonomous vehicle needs tremendous added complexity to deal with all the ways things could go wrong (Koopman & Wagner, 2016).

To avoid failure when allocating functional requirements between safety and non-safety subsystems, creating a distinct, parallel set of criteria that are exclusively safety-related can be helpful. This method can distinguish between issues of performance and optimization ("What is the shortest traveling path?" or "What is the speed for best fuel consumption?") and safety ("Are we going to strike anything?"). Hence, using this method, the collection of requirements would be divided into two pieces. The first set of criteria would be a set of non-safety-related functional needs, which may be presented traditionally or unconventionally, such as a machine learning training set. However, because those potentially unconventional needs are not safety-related, they may be allowed provided traceability and validation are sufficiently covered but imperfectly. The second set of requirements would be solely safety requirements that define "safe" for the system entirely and explicitly, largely irrespective of the intricacies of optimal system behavior. Safe operating envelopes for diverse operational modes are one example of such criteria, with the system free to maximize its performance within the operating envelope. Such envelopes can be employed in at least certain cases (for example, imposing a speed restriction or establishing a minimum following distance). This concept appears to be quite generic but verifying it will take some time (Koopman & Wagner, 2017).

Conclusion:

The automotive sector in the twenty-first century is rapidly expanding its potential, thanks to ongoing technological improvement. This article has studied the impact of the autonomous vehicle on the transportation network. Moreover, we have studied how big data plays a crucial role in the operations of autonomous vehicles. We can fairly conclude that without the collected data about the surrounding of the vehicles and the driving patterns of the driver, autonomous vehicles cannot function. Internet of Vehicles includes all the sensors and all the essential equipment which lead to successful journeys without human interference. The data collected by the sensors are processed in the backend not just to operate the vehicle but to also gather information about the road and traffic conditions. Furthermore, we examined the IoV in the era of big data and the relationship between the IoV and big data. We've proven that IoV can help with big data acquisition, transmission, storage, and computation on the one hand, and that big data can help IoV with network characterization, performance analysis, and protocol design on the other. Such a reciprocal relationship is extremely valuable for tracking the IoV's progress with mutualism to massive data. Furthermore, we have highlighted and enlarged the critical significance of IoV big data in autonomous vehicles, as well as targeted emerging challenges to demonstrate some desired future IoV paths in the big data era.

Work Cited

An overview of Internet of Vehicles. (2014, October 1). IEEE Journals & Magazine | IEEE Xplore. https://ieeexplore.ieee.org/document/6969789/;jsessionid=nj30lRYeNy2xHKk9I6MfoKMgflXt6sLRQT4kFLmXiijAb1VPPg36!-1666311061?tp=&arnumber=6969789

Survey on the Internet of Vehicles: Network Architectures and Applications. (2020, March 1). IEEE Journals & Magazine | IEEE Xplore. https://ieeexplore.ieee.org/document/9088328/;jsessionid=9GD0lfCd0ypG0dxd1ozmk4T-EW1fX3qfjckgSDEKAtr3ca-Y_MbE!-1666311061?tp=&arnumber=9088328

Internet of vehicles in big data era. (2018, January 1). IEEE Journals & Magazine | IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/8232587

Morando, A., Gershon, P., Mehler, B., & Reimer, B. (2021). A model for naturalistic glance behavior around Tesla Autopilot disengagements. *Accident Analysis & Prevention*, *161*, 106348. https://doi.org/10.1016/j.aap.2021.106348

Larsson, A. F. (2012). Driver usage and understanding of adaptive cruise control. *Applied Ergonomics*, *43*(3), 501–506. https://doi.org/10.1016/j.apergo.2011.08.005

Chen, K., & Tomblin, D. (2021). Using Data from Reddit, Public Deliberation, and Surveys to Measure Public Opinion about Autonomous Vehicles. *Public Opinion Quarterly*, *85*(S1), 289–322. https://doi.org/10.1093/poq/nfab021

Fényes, D., Németh, B., & Gáspar, P. (2019). A predictive control for autonomous vehicles using big data analysis. *IFAC-PapersOnLine*, *52*(5), 191–196. https://doi.org/10.1016/j.ifacol.2019.09.031

Sensors and Sensor Fusion in Autonomous Vehicles. (2018, November 1). IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/8612054?casa_token=mUfNgqHedo4AAAAA:S2y5hjOaLepi66N225nzYHPGvKJBG1Hin-DG4H5PNKQcN8vJYjX6hlE1OPrX9NT9orHwO7ogP7w

Baucells, M., & Yemen, G. (2019). Tesla and the Future of Autonomous Driving. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3401222

Endsley, M. R. (2017). Autonomous Driving Systems: A Preliminary Naturalistic Study of the Tesla Model S. *Journal of Cognitive Engineering and Decision Making*, *11*(3), 225–238. https://doi.org/10.1177/1555343417695197

Sadasivam, S. (2015). Autonomous driving — what drives it? *Auto Tech Review*, *4*(9), 22–27. https://doi.org/10.1365/s40112-015-0978-6

Morando, A., Gershon, P., Mehler, B., & Reimer, B. (2021b). A model for naturalistic glance behavior around Tesla Autopilot disengagements. *Accident Analysis & Prevention*, *161*, 106348. https://doi.org/10.1016/j.aap.2021.106348

Collingwood, L. (2018). “Trust in the machine: the case of Autonomous vehicles.” *Journal of Information Rights, Policy and Practice*, *2*(2). https://doi.org/10.21039/irpandp.v2i2.43

Piesnack, S., Frame, M. E., Oechtering, G., & Ludewig, E. (2013). FUNCTIONALITY OF VETERINARY IDENTIFICATION MICROCHIPS FOLLOWING LOW- (0.5 TESLA) AND HIGH-FIELD (3 TESLA) MAGNETIC RESONANCE IMAGING. *Veterinary Radiology & Ultrasound*, n/a. https://doi.org/10.1111/vru.12057

Fényes, D., Németh, B., & Gáspár, P. (2021). Design of LPV control for autonomous vehicles using the contributions of big data analysis. *International Journal of Control*, 1–12. https://doi.org/10.1080/00207179.2021.1876922

Pek, C., & Althoff, M. (2021). Fail-Safe Motion Planning for Online Verification of Autonomous Vehicles Using Convex Optimization. *IEEE Transactions on Robotics*, *37*(3), 798–814. https://doi.org/10.1109/tro.2020.3036624

Qian, L., Xu, X., Zeng, Y., & Huang, J. (2019). Deep, Consistent Behavioral Decision Making with Planning Features for Autonomous Vehicles. *Electronics*, *8*(12), 1492. https://doi.org/10.3390/electronics8121492

Koopman, P., & Wagner, M. (2016). Challenges in Autonomous Vehicle Testing and Validation. *SAE International Journal of Transportation Safety*, *4*(1), 15–24. https://doi.org/10.4271/2016-01-0128

Koopman, P., & Wagner, M. (2017). Autonomous Vehicle Safety: An Interdisciplinary Challenge. *IEEE Intelligent Transportation Systems Magazine*, *9*(1), 90–96. https://doi.org/10.1109/mits.2016.2583491