**Autonomous Driving Vehicles’ Architecture for Computational Intelligence Evaluation**

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**Introduction**

Automated driving systems (ADSs) and autonomous driving (AD) promise numerous practical benefits at a personal and societal level. Within the last decade, billions of dollars have been poured into research and development in the industry, with alluring promises of reaching Level-4 and Level-5 AD (see Table 1 for an explanation of the levels of autonomous driving) by 2025-2030. With these ambitious goals in mind, AD and AD-infrastructure organizations are touting the following benefits: reduced drivers’ stress and increased productivity, mobility for non-drivers, reduced paid driver costs, increased safety, increased road capacity and cost savings, reduced parking costs, reduced energy consumption and pollution, and vehicle sharing support. Examining the current state of AD technological developments and the overall architecture of AD systems gives a holistic look into where the field currently stands, what research directions the field is headed towards, and blockers impeding or slowing AD progress. This paper will examine Computational Intelligence (CI) concepts and advancements in AD to address the barriers for Level-4 and Level-5 AD in the coming years.

Table 1. Levels of Vehicle Automation

|  |  |  |
| --- | --- | --- |
| SAE Automation Category | Vehicle Function |  |
| Level 0 | Human driver does everything. |
| Level 1 | An automated system in the vehicle can sometimes assist the human driver conduct some parts of driving. |
| Level 2 | An automated system can conduct some parts of driving, while the human driver continues to monitor the driving environment and performs most of the driving. |  |
| Level 3 | An automated system can conduct some of the driving and monitor the driving environment in some instances, but the human driver must be ready to take back control if necessary. |  |
| Level 4 | An automated system conducts the driving and monitors the driving environment, without human interference, but this level operates only in certain environments and conditions. |  |
| Level 5 | The automated system performs all driving tasks, under all conditions that a human driver could. |  |

**Vehicle Architecture and Subsystems**

Diagram, schematic

Description automatically generatedThe architecture of a typical self-driving car, seen in Figure 1, illuminates what hardware and software a typical vehicle might be equipped with to support CI developments. The self-driving car in Figure 1 is the Intelligent Autonomous Robotic Automobile (IARA), a modified 2011 Ford Escape that was the first to travel 74 km on urban roads and highways in Brazil.

Figure 1. Software Architecture of Typical Autonomous Vehicle (IARA)

IARA contains a number of hardware components conducive to software development and AD. The steering wheel comes with an actuation subsystem manufactured with the power steering system. The power steering system was modified to add an electronic module capable of sending signals equivalent to those sent by the torque sensor and throttle pedal. The braking system is equipped with an electronic linear actuator that is physically attached, so the brakes can be used normally as well. The gear stick inside of the vehicle is attached to a series of electronics switches and relays that register the car’s current gear. The numerous computers and sensors that drive the autonomous system use an overloaded 330 Volts battery with a DC-DC converter capable of fast-charging. Finally, the vehicle contains a workstation Dell Precision R5500, with 2 Xeon X5690 six-core 3.4 GHz processors and one NVIDIA GeForce GTX-1030, networking gear, two LIDARS (a Velodyne HDL-32E and a SICK LD-MRS), three cameras (two Bumblebee XB3 and one ZED), an IMU (Xsens MTi), and a dual RTK GPS (based on the Trimble BD982 receiver). All these components are routed together so they can be instantly switched between manual driving and AD.

The system’s software architecture can be divided into perception and decision-making systems at the highest level. From start to finish, IARA receives data from the sensors made available through drivers’ modules, sends them to filter modules, filter modules receive input sensor data and other filter modules, and filter modules output processed versions of inputted data. Some key modules are: GNSS module (transforms latitude and longitude data into x, y, and z coordinates), Map Server module (provides offline map to give IARA’s current position), Localizer module (localizes IARA on offline map and generates point clouds from LIDAR to place IARA in 8-dimensions of x, y, z, roll, pitch, yaw, v, and phi), Moving Objects Detector module (detects moving obstacles and their speed), 2D Mapper module (creates online map of path and static/moving obstacles around IARA), ODGM Generator module (generates ODGM from a fused 2D map), Lane Detector module (identifies path markings), Traffic Sign Detector module (detects and recognizes traffic signs), Traffic Light State Detector module (detects traffic lights along path and identifies status of lights), Path Planner module (computes a path from IARA’s current position to goal position), Behavior Selector module (establishes goal for IARA and suggests path(s) to this goal), Motion Planner module (constructs trajectory from current position to goal), Obstacle Avoider module (evaluates current path to change velocity and direction if necessary), Ford Escape Hybrid module (driver of the car), and Health Monitor module (checks for functioning of all modules). With the General Architecture of autonomous driving vehicles (ADVs) laid out, the developmental areas can be examined more effectively and put in context at the grander system level. To help picture the modules needed to support an ADV during actual driving scenarios, Figure 2 is shown below.

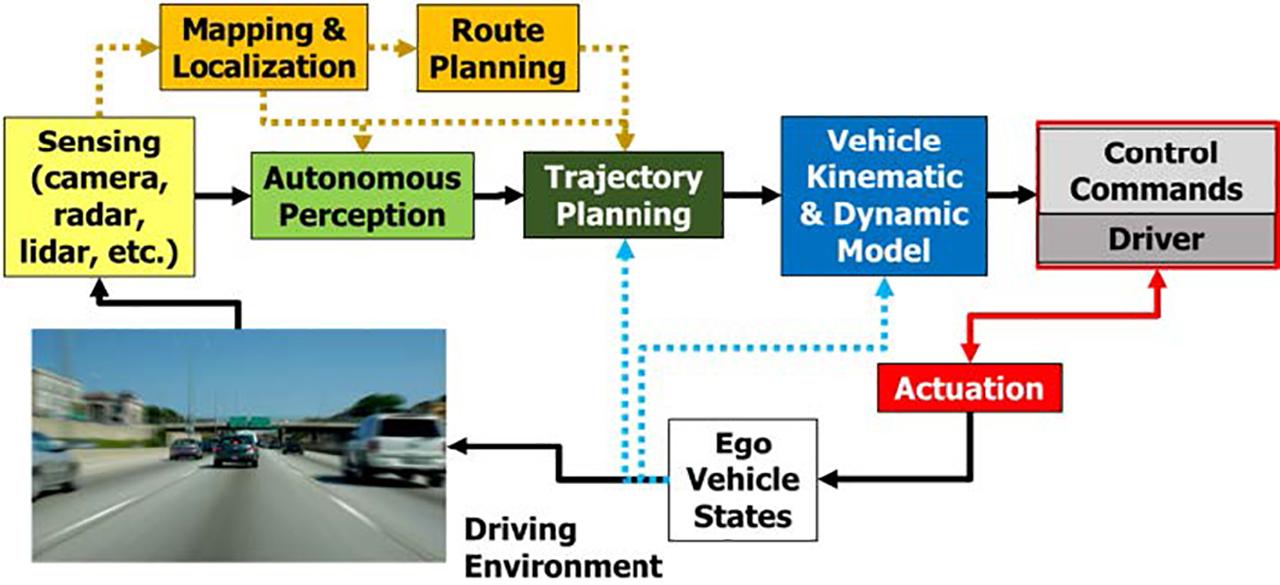


Figure 2. Functional Block Diagram of an ADV

**Functional Groupings of ADVs**

Filtering modules can be lumped together for comprehensive functional evaluations. Two different functions of ADVs, perception and decision making, are differentiated by their vastly different and unique CI approaches. Figure 3, seen below, shows how the complexity and operating conditions in various driving systems may receive different input data and feedback mechanisms. These functional areas elicit different feedback mechanisms and prescribe unique problem-solving frameworks.

Diagram

Description automatically generated

Figure 3. Autonomous Vehicle System Overview and High-Level Functional Groupings

**Perception**

Perception refers to the ability of an autonomous system to collect information and extract relevant knowledge from the environment. Perception of an ADV includes localization, offline and online mapping of unstructured environments, road mapping, moving objects tracking, and traffic signalization detection. Perception-related AV tasks are a LiDAR-only method for color estimation and geometric spatial distributions tied back into image inputs.

**Decision Making**

Due to the complex, dynamic nature of autonomous vehicles, Decision making of an ADV includes route planning, path planning, behavior selection, motion planning, obstacle avoidance, and control. As part of decision making’s planning sub-functions, three tasks have been summarily identified: (1) finding a path, (2) searching for the maneuver, and (3) determining the most feasible trajectory. Decision making generates kinematically and dynamically logical path and velocity profiles for the robotic system to execute. Due to computational constraints, decision making at most simplifies the problem(s) by making assumptions about surrounding vehicles, such as surrounding vehicles keep constant speed or the complexity of any scenario can be gauged by the amount of objects detected. Although decision making works fine on less busy public highways and roads, urban areas provide a unique challenge where decision making intelligence has not caught up to human driving abilities.

**Computational Intelligence Algorithms**

Different algorithms are proposed based on the problems at hand in the AV industry. The ultimate goal of all machine learning (ML) algorithms used in autonomous driving are concerned with monitoring the surrounding environment and accurately predicting the possible changes to that surrounding. Proposed algorithms include supervised, unsupervised, regression, classification, cluster, and decision matrix. Deep Learning is touched upon to show common modern models for perception and decision making.

**Supervised Machine Learning (ML) Algorithms**

Supervised Learning groups and interprets data based only on input data. Classification and regression are both different types of commonly used supervised learning. In supervised models, an algorithm is fed instructions on how to interpret the input data. Self-driving cars prefer unsupervised learning because it allows the algorithm to evaluate training data based on a fully labelled dataset, making supervised learning more useful where classification is concerned. These algorithms essentially keep learning until they reach the desired level that promises minimal errors.

**Unsupervised Machine Learning Algorithms**

Unsupervised learning develops predictive models based on both input and output data. Clustering is one example of unsupervised learning. Unsupervised learning receives unlabeled data and no instructions on how to process it, so the algorithms figure out how to do it on their own. These algorithms know how to make use of the data at hand and no training datasets are needed because when used effectively, they are able to find identifiable patterns within the data. After finding patterns within the data, they divide the data into classes/groups according to their level of similarity between them.

**Regression Algorithms**

Regression algorithms are used for predicting AD events. There are several types of commonly used regression algorithms including Bayesian regression, neural network regression, and decision forest regression. Generally, the relationship between two or more variables is estimated with regression so the effects of variables can be compared on different scales. Three metrics derive their dependencies from regression: (1) the number of independent variables; (2) the type of dependent variables; and (3) the shape of the regression line. The repetitive nature of regression algorithms in their environments form a statistical model between a particular image and the position of a specific object within the image, allowing for quick object detection by sampling 100s or 1000s of images. Regression requires little human intervention and learns at a comparably faster rate than classification.

**Pattern Recognition Algorithms (Classification)**

Advanced driver-assistance systems (ADAS) notably seen in Tesla’s autopilot, obtains images from the surrounding environment and yields an array of images. These algorithms specialize in filtering data obtained through sensors by detecting object edges, and fitting line segments and circular arcs to the edges. Combining the line segments and circular arcs in many different ways, pattern recognition algorithms able to form important features for recognizing an object. Some commonly used pattern recognition algorithms in self-driving cars are support vector machines (SVMs), principal component analysis (PCA), Bayes decision rule, and k-nearest neighbors (KNN).

**Cluster Algorithms**

Cluster algorithms use data points to discover structures. If images are not clear or classification algorithms have misidentified or skipped over images due to low-resolution or few data points, clustering algorithms step in to help with object detection. They define the class of problem and class of methods to establish centroid-based and hierarchical modeling approaches. They try to leverage data structures to best organize the data into groups with relative commonality. K-means and multi-class neural networks are commonly used, general purpose cluster algorithms.

**Decision Matrix Algorithms**

Decision matrix algorithms are used exactly what they sound like they would be used for, for decision making. These algorithms identify, analyze, and rate the performance of relationships between sets of values and information in them. By doing so, they help determine the moves of autonomous vehicles, such as when a car may need to make a turn or when it needs to brake or accelerate. Decision matrix algorithms’ predictions combine to generate an overall prediction while minimizing the possibility of errors.

**Deep Learning Models**

Deep Learning differs from machine learning in that deep learning relies on layers of ANNs while machine learning uses structured data. Deep learning does not require human intervention, as multilevel layers in neural networks place data in a hierarchy of different concepts which learn from their own mistakes; this also makes deep learning reliant on having vast amounts of data which AD has struggled in the past with but is less of an issue heading into the 2020s. The most common deep learning methodologies applied to AD are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Reinforcement Learning (DRL). Deep CNNs are mainly used for processing spatial information, such as images, and viewing image feature extractors and universal non-linear function approximators. RNNs specialize in processing temporal sequence data, such as text, or video streams. They differ from CNNs in that they contain a time dependent feedback loop in memory. DRL is used to refer to an autonomous driving task, using partially observable Markov decision process (POMDP). DRL generally interacts with the surrounding environment, learning from anomalous fail-safe scenarios such as a crash, to improve on discrete control tactics and also makes use of simulated driving environments.

**Algorithmic Applications and Foreseeable Challenges**

With all the strides made to speed up the race to Levels 4 and 5 autonomous driving, there are still great hurdles to overcome. At a high level, there are five main obstacles: (1) the technology and CI applications including safety, security, communication, and security, (2) laws including liability, (3) pricing, (4) human factors, and (5) future impact on jobs and death rates. The content of this paper examines (1) to see what challenges are present with the CI technology in AVs.

One concern with AD is that Level 3 is not deployable at a fleet-level. Some considerations for determining fleet level impact include understanding the possible failures, understanding the context within the wider system, defining assumptions regarding system context and the environment in white fleets are likely to be used, and defining what safe behavior means at a macro level which also includes non-functional constraints. Deploying at a fleet level for even Level 3 involves creating an infrastructure that can support routine and semi-regular charging, assuming AVs in the future are electric vehicles (EVs). At a fleet level, this also crosses over into more robust security requirements needs for unethical hackers and increased network capabilities greater than what has been produced by minimally latent and scalable tech giant cloud services such as Amazon Web Services, Microsoft Azure, or Google Cloud.

Second, advancements need to happen with both the hardware and software. The various sensors used by AVs demand a much greater awareness than what is currently present. Right now, the solution is to keep vertically scaling up with the amount of sensors. Each sensor added comes with a trade-off. For example, LiDAR is very effective at short ranges but significantly weakens past 200 meters. SONAR and radar on the other hand can account for LiDARs shortcomings but it is a balancing act then between sensor additions, system complexity, and allotting proper CPUs without driving up costs. From more of a CI perspective, as mentioned earlier the algorithms and models still struggle to compensate for human’s natural abilities in “seeing” the environment around them and adapting to anomalous situations. The computing power needed to conquer more advanced, less common challenges such as a deer darting out in front of the vehicle on the highway or quick reaction timings with emergency braking are exponentially more difficult to model than a car cruising on an empty highway with no anomalous events occurring.

Increased software complexity is the third and largest problem with AD. Research efforts are split between advancing unique algorithms/models and testing the increased sensor complexity with software needed to process large amounts of real-time data. As sensor hardware adapts to changing conditions better, the number of input features exponentially grows to account for more variable driving scenarios making the system’s operations more costly. To minimize latency, modern AVs contain at least 1 billion lines of code (SLOC) with research AVs containing multi-billions SLOC. Early AV development efforts aligned more with embedded processing, however, with the enormous computing powers needed to process the data AVs have transcended to align more with server performance. Discrete CPUs have been replaced with clusters of application processors and accelerators in more performant multicore systems on a chip (SoCs), shifting the underlying fundamental software architectures. Even with the need for multicore SoCs, there will still be a need to support mixed-critical applications on a single SoC to support safety objections. The complexity far outweighs their closest related autonomous systems, passenger jets. In moving from prototypes to full scale product for Levels 4 and 5 AD, a common belief is that power consumption needs to be reduced 10x and compute size by 5x.

**Conclusions**

In summary, CI applications will continue to play an important role in the development of AVs for their role of interacting with the vehicles’ hardware and increasing data. The field of AD is solving problems that have not been solved before at the crossroads between physics, computer science, CI, electronics, mechatronics, aerodynamics, industrial planning, and many other fields. The hardware and software architecture shown in the beginning for a typical ADV will only to continue to grow in complexity as more hardware is added to account for various driving scenarios and large-scale deployment. The driving scenarios will be accounted for in CI advancements in deep learning and to a lesser extent, machine learning. The algorithms and ML/DL modelling techniques described in this paper lay the foundation for the application of more advanced techniques in various AV areas such as object detection, object labeling and tracking, and domain adaptation. A fundamental understanding of what ML/DL “tools” are available to advancing deep learning architectures is needed to improve on the functional tasks of AVs, for both perception and decision making. Since driving is such a safety-heavy task, AV compliance researchers are hoping to automate as much of the driving as possible to take human error and inconvenience out of the equation. Projections show incremental leaps in knowledge, between the interacting software, hardware, and CI that will facilitate the hopeful promise of Levels 4 and 5 driving by 2030. The challenges are numerous, ranging from government policy and safety to ethical concerns, however, envisioning a future where CI is able to play such a prominent role in routine everyday tasks makes overcoming the barriers worthwhile.

**References**

[1] Anderson, J., Kalra, N., Stanley, K., Sorenson, P., Samaras, C., & Oluwatola, T. (2016, March 22). Self-Driving Vehicles Offer Potential Benefits, Policy Challenges for Lawmakers. Retrieved from https://www.rand.org/pubs/research\_reports/RR443-2.html

[2] Ang, M. (2017, February 17). Perception, Planning, Control, and Coordination for Autonomous Vehicles. Retrieved from https://www.mdpi.com/2075-1702/5/1/6

[3] Badue, C., Guidolini, R., Carneiro, R., Azevedo, P., Cardoso, V., Forechi, A., … De Souza, A. (2019, October 02). Self-Driving Cars: A Survey. Retrieved from https://arxiv.org/abs/1901.04407

[4] A Brief Survey of Autonomous Vehicle Possible Attacks, Exploits, and Vulnerabilities. (2018, October 03). Retrieved from https://deepai.org/publications/a-brief-survey-on-autonomous-vehicle-possible-attacks-exploits-and-vulnerabilities

[5] Chen, T., Li, Z., He, Y., Xu, Z., Yan, Z., & Li, H. (n.d.). From Perception to Control: An Autonomous Driving... Retrieved from https://arxiv.org/pdf/1909.00119v1

[6] Grigorescu, S., Transnea, B., Cocias, T., & Macesanu, G. (2020, March 24). A Survey of Deep Learning Techniques for Autonomous Driving. Retrieved from https://arxiv.org/abs/1910.07738

[7] IEEE Spectrum. (n.d.). Accelerating Autonomous Vehicle Technology. Retrieved from https://spectrum.ieee.org/transportation/self-driving/accelerating-autonomous-vehicle-technology

[8] Issues in Autonomous Vehicle Testing and Deployment. (n.d.). Retrieved from https://crsreports.congress.gov/product/pdf/R/R45985

[9] Janai, J., Guney, F., Behl, A., & Geiger, A. (2019, December 17). Computer Vision for Autonomous Vehicles: Problems, Datasets, and State of the Art. Retrieved from https://arxiv.org/abs/1704.05519v2

[10] Kane, F. (2020, December 08). Machine Learning vs. Deep Learning: What’s the Difference? Retrieved from https://blog.udemy.com/machine-learning-vs-deep-learning-whats-the-difference/

[11] Katrakazas, C., Quddus, M., Chen, W., & Deka, L. (2015, November 03). Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. Retrieved from https://www.sciencedirect.com/science/article/pii/S0968090X15003447

[12] A Survey of Autonomous Driving: Common Practices and … (n.d.). Retrieved from https://arxiv.org/pdf/1906.05113v2.pdf

[13] Testing and Verification of Safe Network-Based Driving Algorithms. (n.d.). Retrieved from https://deepdrive.berkeley.edu/project/testing-and-verification-safe-network-%C2%ADbased-driving-algorithms

[14] Wei, J. (2020, October 16). A Behavioral Planning Framework for Autonomous Driving. Retrieved from https://www.ri.cmu.edu/publications/a-behavioral-framework-for-autonomous -driving/

[15] What Are the Biggest Driverless Car Problems? (2020, January 28). Retrieved from https://9clouds.com/blog/what-are-the-biggest-driverless-car-problems/