Next Generation Distributed and Networked Autonomous Vehicles: Review

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***Abstract*—Designing next generation autonomous system requires careful architecture planning, data handling, multi-layered distributed computing platform, and ethical consideration for better decision making. This paper provides a comprehensive survey of existing literature and futuristic road map in the design of autonomous systems.**

Keywords—autonomous vehicles, decision-making, decision chains, artificial intelligence.

I. Introduction

Automation has radically improved the efficiency, and the rate at which goods are manufactured, while information technology has assisted on how services are rendered [1]. However, such a paradigm shift has yet to take place in the transportation industries. Even though automation technologies like cruise control and auto pilot are commonplace in ground and aerial vehicles today, they are limited in their functionalities and circumstances of usage. Hence, the need for autonomous vehicular technologies without humans in the loop are growing. Developing Autonomous Vehicles (AV) has its own unique challenges. First, they must work in highly complex and dynamic environments; Secondly, they should not fail in situations where limited information is available, and they must provide meaningful responses to inputs that were unforeseen at design time.

Recent studies like [2] from RAND Corporation point out the myriad of positive impact that AV's can have on a society. In this regard, developing AV's are seen as next logical step for innovation to progress. Fortunately, a large number of firms have invested nearly 80 billion dollars over the past 4 years for the development of AV technologies [3]. The most notable successes can be seen in the case of self-driving cars, where automobile manufacturers like Tesla [4], technology companies like Google [5] and NVIDIA, ride sharing platforms like Uber, and startups like NuTonomy, have demonstrated fully autonomous prototypes. Aerial vehicles (or drones) startups like Intelligent Flying Machines [6] and Matternet are offering commercial products based on fully autonomous drones.

There is also a need to have some commonly accepted standards to quantify autonomy in a given AV. The US Army Corps of Engineers devised a framework called the Autonomy Levels for Unmanned Systems (ALFUS) to quantify autonomy for a generic unmanned vehicle [7]. It proposes to combine performance indices from three different metric groups, namely environment complexity, mission complexity and human independence and represent autonomy level on a scale of 0 to 10 as seen in Fig. 1. In case of commercial and passenger ground vehicles, there are officially 6 levels of automation that have been defined by Society of Automotive Engineers (SAE), starting with no automation to fully autonomous (where the steering wheel is optional) [8].

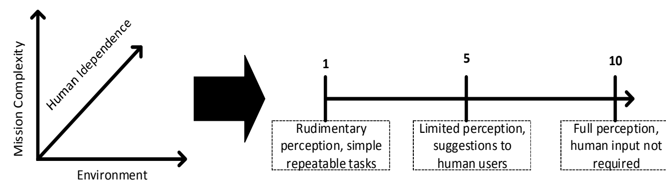

Fig. 1. Quantifying Autonomy

II. Decision Chains and Design Choices

Like any other design for a cyber-physical system (CPS), designing and operating an AV require a multi-facet choice approach (See Fig. 1). The most important of these is probably the decision chains within an AV. In a human driven vehicle, the actuators (*e.g., steering, propulsion etc.*) are directly under the control of a person, either directly or through remote control. In an AV, the actuators are under control of algorithms which process the measurement data from an array of sensors (*e.g., cameras, radar, lidar, or ultrasonic*). This may be referred to as the decision chain as seen in Fig. 3.

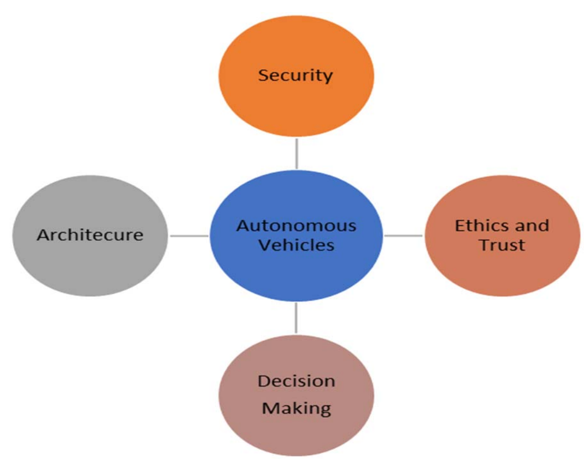

Fig. 2. Design Choices in an Autonomous Vehicle.

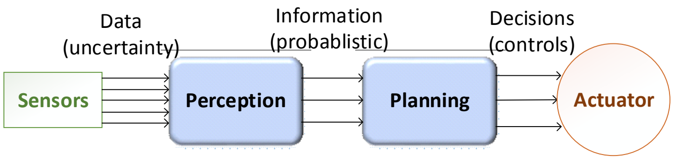

Fig. 3. Decsions chain in autonomous vehicle

Perception involves transforming the sensory data to useful information, and developing a contextual understanding of the environment around an AV. Planning refers to the decision that must be made by AV to execute its goal from a given start position. Control of AV's are the ability to execute the decisions that are made through proper planning.

Algorithms needed for creating decision chains for AV's have existed for many decades, but the recent progress towards commercial deployment can be attributed to a couple of important technological developments.

a) Computing hardware: The decision making software pipeline may have multiple algorithms running parallely. The development of multi-core CPU's and General purpose GPU computing have enabled algorithms to run in parallel with minimum latency. More recently embedded hardware specifically designed for AV's have been announced by NVIDIA [9].

b) Advances in computer vision: Visual stimuli is the primary sensory input which humans use to drive vehicles. However, computer vision has always been a challenge until 2012 (and subsequent years) when the use of deep learning produced remarkable results. Now nearly every prototype AV using cameras use a deep learning algorithm to for perceiving its surroundings.

The decision chains in AV's are ultimately Artificial Intelligence (AI) programs. Hence, AI approaches such as Rule-based (e.g., expert system), Formal logic [10], Supervised Machine learning [11], Reinforcement learning [12], Evolutionary algorithms [13], and Graph and Tree Search methods [14] are potential platforms for developing algorithms that can aid in decision-making. A summary of most widely used and algorithms within these approaches are illustrated in Fig. 4.

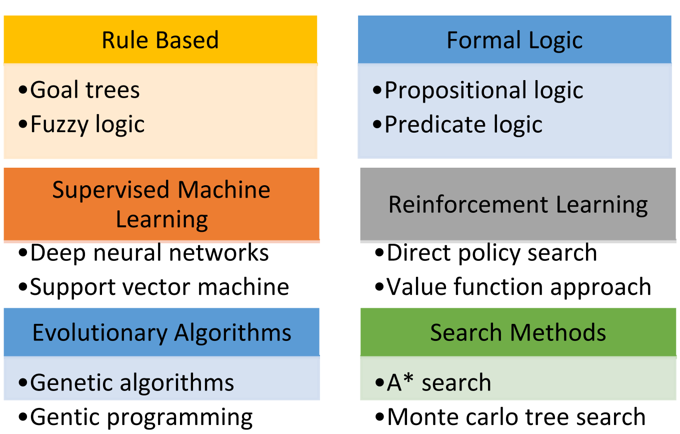

Fig. 4. Futuristic AV Algorithms

Recent advances in AV technology has improved both software and computing hardware capacity to collect, process and store more data. Thus, enabling AV's to operate in cloud based Internet of Things (IoT) architecture, and high performance distributed computing environment.

The tasks to transform sensory data to meaningful information in the perception block uses Machine learning approaches. However, recent advances in deep learning (DL) have prompted researchers to apply DL for planning tasks. The earliest application of neural networks to control a self-driving car can be found in [15]. Researchers at Microsoft used Reinforcement learning (RL) combined with a heuristic search algorithm called Monte Carlo tree search to develop an autonomous glider [16]. Researchers in Zurich used a Convolutional neural network (CNN) to predict the direction of translation movement of a quadcopter using only the camera imagery as input parameter. The quadcopter could autonomously navigate itself through a forest trail [17] after sufficient training. This is called as an end-to-end system, because perception, planning, and action all occur within a single CNN (*i.e. there are no separate algorithms for these functions*). An enhanced version of this concept was developed by researchers at NVIDIA in [18].

Formal logics are used to describe the complex rules of behavior; verify specifications are satisfied; and synthesize a control system to behave as per specification. Early literature focused on verification i.e. use Formal logic to check whether the decision-making algorithms make logically plausible decisions over a wide range of scenarios. A few well-cited examples in literature are: [33] where Formal logic was used to check the software modules in the 'Alice' autonomous vehicle that was part of the DARPA 2008 grand challenge, [36] where the properties of a simulated model of an autonomous vehicle agent was tested and verified using Linear Temporal logic (LTL).

Formal logics has also been used in the synthesizing control systems for AV's and robots. An early work sought to create a hybrid controller that integrate both high-level decision making and low-level goals for autonomous robots [19]. The work in [20] described the use of temporal logic to generate mission plans for a Unmanned Aerial Vehicles (UAV). It also described how feedback during the execution of the plan can be used to enhance the reasoning capability of the system. The practical feasibility of the system was demonstrated by deploying it in a laboratory scale UAV. The dissertation work by Ulusoy [21] discusses in details the use of temporal logic to synthesize planning and control algorithms for autonomous systems with a focus on robots. The path planning problem was solved using a constraint approach while the control problem was solved using a receding horizon concept. The most substantial work on applying formal logic for autonomous vehicles was by Wongpiromsarn et al. and has found practical application in commercial self-driving cars [22]. Her dissertation work [23] developed a specification language langue using temporal logic for the embedded control system used in autonomous vehicles in an urban environment. The work described both verification and synthesis of the embedded control software. The work in [24] focuses on the synthesis of a control structure consisting of a goal generator, trajectory planner, and a continuous controller.

A receding horizon framework is proposed to solve the problem of interfacing the discrete decision-making process with the continuous physical system. The work in [25] uses the same methodologies with emphasis on formal specification of traffic rules in an urban environment and synthesizing a controller for the same. The same author provides an overview of techniques that combine formal logics with control theory for autonomous systems [26].

III. Distributed Architecture

A cyber-physical system (CPS) like an AV may take on a centralized or distributed architecture depending upon how it's control, data, and processors are organized [27],[28]. A system may be said to be distributed, if at least one of its physical component is distributed.

Research into distributed robotic systems have been pursued since the 1980's and [29] gives a taxonomy of the various methodologies in use. A more recent work in [30] provides an extensive survey of the current trends in multi-robot motion-planning algorithms. A decentralized control algorithm was proposed in [31] to transport a single object using a pair of robots without having to share locational information between them. In [32], a paradigm was proposed to assign specific roles to each robot in a group of robots, and have the robots dynamically exchange roles. A distributed architectures for a guided ground vehicle was modeled using Petrinets in [33]. The work in [34] described the design and building of a prototype distributed architecture for Unmanned Aerial Vehicles (UAV's). They also demonstrated experimental flights with the UAV using this architecture.

AV's are expected to outperform a human driver or controller in terms of every performance metric. Hence, the need to have an architecture where the different systems and sub-systems in the AV can utilize available algorithms for optimal operations, data and processors in a manner that are cost-efficient, and perform energy aware computations as seen in Fig 5.

There are considerable advantages to use a distributed architecture platform for AV's. Two intuitive reasons are: a) various systems within an AV are physically separated. b) the individual AV may be part of a cluster of AV's, like in the case of AV's used for ride sharing services [35] or drones used in warehouse management [6]. A distributed architecture may be a means to efficiently increase knowledge, computing, and perspective of an AV. Another advantage is modularity wherein it might be possible to scale up the problem-solving capacity of the system.

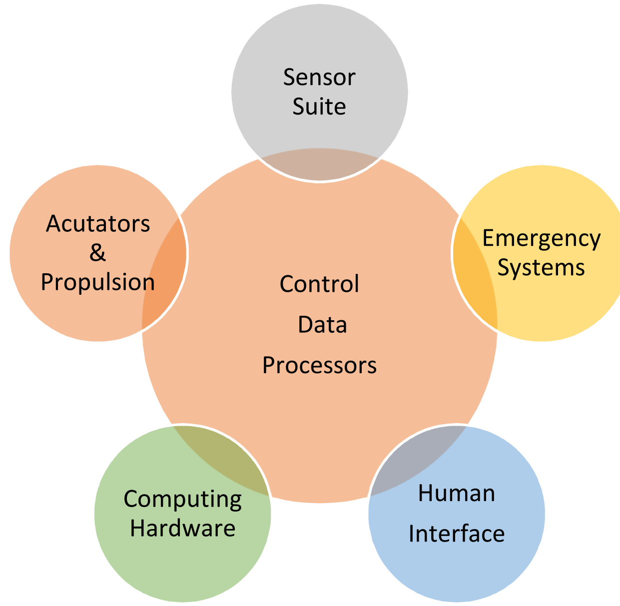

Fig. 5. Control, data, and processor shared by different sub-systems in AV

IV. Trust and Ethicality

Trust and ethics are concepts that are associated with sentient entities. But the capability of AV's to act without human intervention require mathematical representations of these concepts for interacting with human and AV's.

A. *Quantifying trust Distributed AV Architectures*

Trust in an automated or autonomous system has been described as the users willingnes to believe information provided by the systems and use it to achieve a goal [36]. The actions and decisions in an AV are made by complex hierarchical algorithms which may appear like a black box to the human observer and lead them to question it's trustworthiness [1],[37]. Similarly, machines must establish trust in the actions and information coming from human coworkers. Two approaches can be seen in literature for devloping trust between humans and machines. The first is to through design methodology i.e. using a human centred design approach. Second way to develop mathematical models that can quantify trust. The work in [38] gives a thorough review of human centred design and their applications to autonomous systems. This approach seek to understand when, and why humans would trust a machine, and hence involves both engieering and psychology.

The permeation of information technology means that humans already trust information originating from machines especially in the field or e-commerce and internet banking. The techniques used to ensure trustworthiness here can be applied to AV's as welel. Early works like [39] tried to solve the problem of the dependability of a given information sources in an uncensored multi-agent system using the Bayesian method. Later works have focused on developing trust models in the field of e-commerce and cloud computing [40]. In [41] the trustworthiness of an IT system was evaluated by applying a set of propositional logic rules on information about its components and subsystems. The work by Ries in [42] details the development of the Certain Trust Model (CTM) for selecting of interaction partners for an entity in the cloud. For this purpose, evidence gained from past interaction partners were used to create a Bayesian trust model. In [43] Fuzzy logic was used to create a trust evaluation model using Fuzzy membership functions and fuzzy linguistic variables. The work in [44] focuses on quantifying trust in autonomous vehicles using statistical formal verification method. An attack on the sensors in the autonomous vehicle is simulated to test the effectiveness of the algorithm.

B. *Ethical sub-systems in AV decision chains*

Even though humans are not integral to the operation of the AV, the lack of a human element does not preclude or excuse the AV from adhering to moral standards and exhibit ethical behavior [45]. Hence, the need for algorithms that keep a tab on the ethicality of the decisions taken by an AS. Fortunately there are initiatives like IEEE Global Initiative for Ethical Considerations in Artificial Intelligence and Autonomous Systems with the goal to educate, train and empower engineers and scientists as well as develop operational standards [46]. Practicaly this would mean accomodating sub-systems within the decision making chains of AV to conform with commonly accepted ethical norms. The work in [47] proposes two approaches that may be used based on experience with combat robots:

a) Ethical governor: A component that acts as kind of gate between the planning system and the actuators within the AS, which can intervene when necessary to prevent an unethical response. For the governor to act or not act, it needs to compute the ethics of the planned action using methods like those proposed in [48]. The work in [49] has similar concepts but proposes using formal specifications for the ethical behavior of an AS which can be used to rank multiple plans of actions.

b) Ethical adaptor: This approach stems from the philosophical idea that the feeling of 'guilt' may induce a human person to have ethical behavior. In case of an AS, any ethical violations due to the actions of the AS should cause a quantifiable 'guilt' value (which may be modeled using methods like [50]) to accrue over time and influence future decisions.

An often overlooked consideration is with regard to the intrusion on individual privacy that is an unforseen consequence of the large number of sensors attached to the AV. In case of a self-driving car it might be just video images of neighbouring cars, and it's passengers, while in case of a UAV it might be the land and propoert on the ground below. Recently this topic has been gaining intrest from legal professionals and media [51].

V. CYBER SECURITY

Like in any CPS, the software in an AV is vulnerable to hacking [52]. The potential harm that can be caused by a hacked AV are greater than a personal computer However, isolating the AV from outside networks is challenging, as they have to interact with systems of systems (SoS) approach outside the network of operations. This paper discusses state-of-the work in this context.

One of the biggest threats that society will face as transportation transforms in the coming years is vehicle cybersecurity. It is a topic about which much is still unknown, even among those working at the cutting edge of the industry; vehicle connectivity is a new phenomenon and the technology continues to evolve rapidly. One of the central challenges in vehicle cybersecurity is that the various electrical components in a car (known as electronic control units, or ECUs) are connected via an internal network. Thus, if hackers manage to gain access to a vulnerable, peripheral ECU — for instance, a car's Bluetooth or infotainment system — from there they may be able to take control of safety critical ECUs like its brakes or engine and wreak havoc. Cars today have up to 100 ECUs and more than 100 million lines of code — a massive attack surface. Further complicating matters, auto manufacturers source ECUs from many different suppliers, meaning that no one player is in control of, or even familiar with, all of a vehicle's source code. The threat of automotive cyberattacks will only loom larger as society transitions to autonomous vehicles. But even before autonomous vehicles become widespread, car hacking is already a very real danger: In 2014, more than half of the vehicles sold in the United States were connected, meaning that they are vulnerable to cyberattacks. The solution is to design a multi-layered cyber aware security architecture.

An ongoing policy issue is the future of dedicated shortrange communications (DSRC), as manufacturers want to commercialize vehicles with more advanced autonomous systems. DSRC can allow for limited, short range communication—often less than one kilometer—via wireless links that provide for vehicle-to-vehicle (V2V), vehicle-to roadside (V2R), and vehicle-to-infrastructure (V2I) communications. DSRC, combined with the full "V2X" array of applications, can allow for safety-related capabilities such as collision avoidance and information about operating conditions, as well as convenience-related capabilities such as traffic rerouting, vehicle dispatch, and commercial transactions. For fully autonomous vehicles, DSRC is essential as it can be integrated with radar and LIDAR sensors, GPS navigation, and other onboard capabilities to network with other vehicles to create a holistic image of traffic patterns, weather, road conditions, obstructions, and other pertinent information [53].

VI. FUTURE TRENDS

AV's have an exciting future with some projections indicate that the revenue stream may be worth upto $7 trillion by 2050. Drones, cars and machine to machine interface generate lots of data from their onboard sensors. There will be a necessity to develop more efficient hardware and software pipeline to compress and store such volumous data for archiving and advanced data analystic applications to extract useful information like driving behaviour from this data. Other potential areas in need of solutions are verification and validation algorithms for certifying autonomous systems, rendering down data, human factors, image processing and vision technologies.

VII. Conclusion

This work outlined the key design decisions that are relevant to the AV's, namely decision chains, architecture, trust and ethicality, and cyber security. The challenges involved in these design decsions were explored and the important literature providing solutions were outlined. An overview of potential research opportunities related to AV's was provided. Inorder to drive the area of AV research, effective policies and regulations are needed. Moreover a change in mindset among researchers and the general public is required to take full advantage of AV technology.

TABLE I. Trends in Surveyed Literature

Features	***Reference***	***Key technologies***
Decision chains	[16]-[19],[20]-[27]	Perception or end to end systems using deep learning, Planning using Search trees, Formal logic and Reinforcement learning
Architecture	[30] – [35]	Distributed architecture is prevalent
Trustworthiness	[38] – [44]	Bayesian inference and Fuzzy logic used to model trust
Ethics	[47] – [50]	Ethical governors or Ethical adaptors, privacy issues
Cyber Security	[53-56]	Regulations on Electronic Control Units (ECUs), flight management and control, and indoor localization systems, cyber-attack forecasting.

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