A Review on Fully Autonomous Vehicle

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Abstract - *Autonomous vehicles are expected to play a key role in the future of urban transportation systems, as they offer potential for additional safety, increased productivity, greater accessibility, better road efficiency, and positive impact on the environment. Research in autonomous systems has seen dramatic advances in recent years, due to the increases in available computing power and reduced cost in sensing and computing technologies, resulting in maturing technological readiness level of fully autonomous vehicles. The objective of this paper is to provide a review and recent development in the domain of autonomous vehicle.*

Key words - autonomous vehicles; localization; perception; planning; automotive control; multi-vehicle cooperation

INTRODUCTION-

Autonomous vehicle technology has been a major research and development topic in the automotive industry during the last decade. The technologies developed in the automotive industry also has direct applications in construction, mining, agricultural equipment, seaborne shipping vessels, and unmanned aerial vehicles (UAVs). Significant R&D activities in this area date back three decades. Despite the heavy intensity of investment in technology development, it will still take a few decades before an entirely autonomous self-driving vehicle navigates itself through national highways and congested urban cities [1]. People have been trying to make self-driving cars, since the invention of the car. The history of automated driving from early stages to automated highways and automated vehicles, are reviewed in [2]. A brief history of major autonomous cars development is shown in Fig. 1.

Figure 1. History of Autonomy in ground vehicles ([3,4,5,6,7])

The core competencies of an autonomous vehicle software system can be broadly categorized into three categories, namely perception, planning, and control, with the interactions between these competencies and the vehicle's interactions with the environment depicted in Figure 2. Also, Vehicle-to-Vehicle (V2V) communications can be leveraged to achieve further improvements in areas of perception and/or planning through vehicle cooperation.

Perception refers to the ability of an autonomous system to collect information and extract relevant knowledge from the environment. Environmental perception refers to developing a contextual understanding of environment, such as where obstacles are located, detection of road signs/marking, and categorizing data by their semantic meaning. Localization refers to the ability of the robot to determine its position with respect to the environment. Planning refers to the process of making purposeful decisions in order to achieve the robot's higher order goals, typically to bring the vehicle from a start location to a goal location while avoiding obstacles and optimizing over designed heuristics.

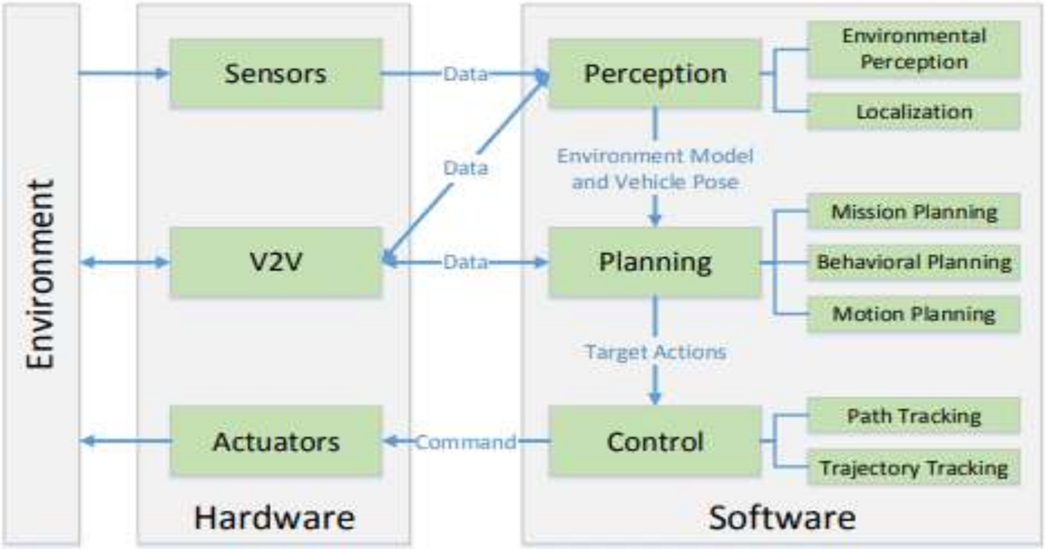

Figure 2.-. A typical autonomous vehicle system overview, highlighting core competencies

The following sensors that measure conditions outside the vehicle, and vehicle position relative to its environment are essential in driving assist systems and autonomous vehicle technologies: Vision, lidar, radar, ultrasonic range, GPS, and inter-vehicle communication. The latest generation of Driver Assist Systems (DAS), also called Advanced Driver Assist Systems (ADAS), defines and controls trajectories beyond the current request of the driver, i.e. overriding driver commands to avoid a collision. All these sensors have overlapping and complementary capabilities. Data fusion strategies that combine real-time information from these multiple sensors is an important part of the embedded control software. Actuation technologies, i.e. computer control steering, throttle, transmission, and braking, are mature and do not present any R&D challenges. The embedded control software development (that includes data fusion from sensors, inter-vehicular communication, real-time cloud computing support) is the key technical challenge.

SENSORS- Different sensors and systems are used for navigation and control of the autonomous vehicle . Prominent sensors such as GPS, radar, vision, ultrasonic and inertial measurement unit, their working principle and usage are discussed in the following sections.

Radar- Radar (Radio Detection and Ranging) transmits electromagnetic pulses and senses the echoes to detect and track objects. Echoes sensed vary in frequency depending on the speed of the object. Radar can measure the relative distance, velocity, and orientation of the object [8.9]. In case of monostatic radars in which the transmitter and receiver are located at the same location, range of the target is measured by using the round trip travel time of a pulse, times the speed of light divided by two. They are typically available for short (≈ 30), medium (≈ 60) and long-range (≈ 200 m) distances and range from 3 MHz (Very long range) to 100+ GHz (Short range) frequencies (Fig.4). Radar requires less computing resources compared to vision or LIDAR. Typical application include lane keeping, advance cruise control, object detection, etc [10].

GPS- Global positioning system (GPS) is used to locate the position of a GPS receiver (x,y,z coordinates) using four or more geostationary satellites. These satellites maintain their position relative to earth and broadcast reference signals. A GPS receiver on earth deciphers the actual location within meters accuracy. However, the so called "differential GPS" can pinpoint a location within centimeter accuracy which is necessary for navigation of autonomous vehicle. GPS consists of three segments: space, control, and user segments. The space segment includes the satellites, control segment manages and controls them and user segment is related to development of user equipment for both military and civil purposes [11]. GPS based navigation application are greatly used to accurately predict the vehicle location with respect to map which is known as localization. However GPS based navigation are inaccurate and can lead to ghosting phenomena.

Vision- Vision system is composed of a camera and image processing unit . A typical camera is a combination of focusing lens and array of photo-detectors for each pixel in the field of view (FOV). The array of photo-detectors send pixel information to image processing unit. This unit processes the information based on certain algorithms to detect desired objects. Vision sensors capture more visual information, hence tracking the surrounding environment more effectively than other sensors. They are categorized into mono and stereo types. Mono camera systems are often used for lane marking, lane edge detection, basic object detection, road sign detection and localization. Multiple or Stereo camera systems provide depth for objects detection. Their primary advantage are their low-cost, off-the-shelf components and their software implementation. Their primary disadvantage is handling a full range of ambient and uncontrolled conditions such as lighting, shadowing, reflection, weather, dust, smoke.

Inertial Measurement Unit(IMU)- A moving vehicle can experience linear and rotational motions along x, y, and z-axes: lateral, longitudinal, and vertical which can be measured by inertial measurement unit including linear and angular accelerations. This information is used to improve GPS measurements. IMU includes accelerometers and gyroscopes.

Ultrasonic Range- Ultrasonic sensors are short range sensors (typical ≈ 2 m) which send an ultrasonic pulse wave and detect echoes returned from the obstacles using transmitter-receiver pair. These are mainly used in relatively low speed ADAS modules like parking space detection and assistance [12] and obstacle detection during congested traffic conditions [13]. They are reliably detect under any weather conditions like rain, snow and winds. However they have range limitation which restricts them to be used as OEM vehicle sensors.

PERCEPTION-

Environmental Perception- Environment perception is a fundamental function to enable autonomous vehicles, which provides the vehicle with crucial information on the driving environment, including the free drivable areas and surrounding obstacles' locations, velocities, and even predictions of their future states. Based on the sensors implemented, the environment perception task can be tackled by using LIDARs, cameras, or a fusion between these two kinds of devices. Some other traditional approaches may also involve the use of short/long-range radars and ultrasonic sensors, which will not be covered in this paper. Regardless of the sensors being implemented, two critical elements of the perception task are (i) road surface extraction and (ii) on-road object detection.

LIDAR- LIDAR refers to a light detection and ranging device, which sends millions of light pulses per second in a well-designed pattern. With its rotating axis, it is able to create a dynamic, three-dimensional map of the environment. LIDAR is the heart for object detection for most of the existing autonomous vehicles. Figure 3 shows the ideal detection results from a 3D LIDAR, with all the moving objects being identified.A high-end LIDAR sensor can measure multiple distances per laser pulse which is helpful to see through dust, rain and mostly transparent surfaces such as glass windows and porous object like wire fences. To reduce the signal to noise ratio, a higher power laser generation is desired but in order to prevent damage to the human eye, a laser power of 905nm is used to achieve desired range with low duty cycle.. Current cost of LIDAR sensor is relatively high and there are some issues with the long-term reliability of their mechanical scanning mechanisms. They have been used heavily in research applications, but not widely used in automotive OEM safety systems until recently.

In a real scene, the points returned by the LIDAR are never perfect. The difficulties in handling LIDAR points lie in scan point sparsity, missing points, and unorganized patterns. The surrounding environment also adds more challenges to the perception as the surfaces may be arbitrary and erratic. Sometimes it is even difficult for human beings to perceive useful information from a visualization of the scan points.

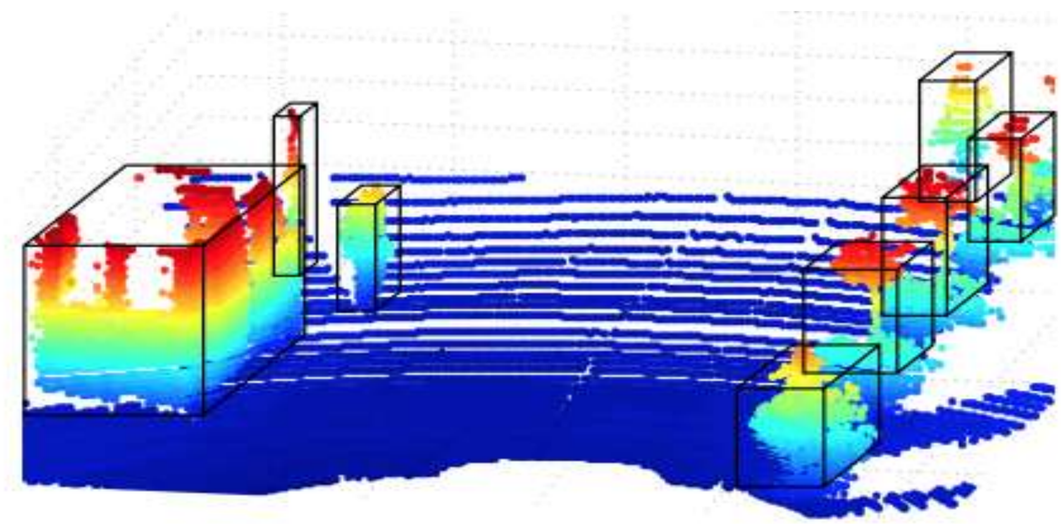

Figure 3- The ideal detection result from a 3D LIDAR with all moving objects detected, adapted from [14].

Representation- The output from the LIDAR is the sparse 3D points reflected back from the objects, with each point representing an object's surface location in 3D with respect to the LIDAR. Three main representations of the points are commonly used, including point clouds, features, and grids [15].

Point cloud based approaches directly use the raw sensor data for further processing. This approach provides a finer representation of the environment, but at the expense of increased processing time and reduced memory efficiency. To mitigate this, usually a voxel-based filtering mechanism is applied to the raw point cloud to reduce the number of points, e.g., [16,17].

Segmentation Algorithm- To perceive the 3D point cloud information, normally two steps are involved: segmentation and classification. Some may include a third step, time integration, to improve the accuracy and consistency. Segmentation of point cloud is the process of clustering points into multiple homogeneous groups, while classification is to identify the class of the segmented clusters, e.g., bike, car, pedestrian, road surface, etc.

As summarized in the survey paper [18], the algorithms for 3D point cloud segmentation can be divided into five categorizes: edge based, region based, attributes based, model based, and graph based. In this section, we will provide supplementary reviews to reveal the recent development in this field. As a result, a new category is identified, which is based on deep learning algorithms.

Detection Algorithm- After the segmentation, each cluster needs to be categorized into different objects. The information embedded in each cluster is mainly from spatial relationship and the LIDAR intensity of the points, which has very limited use in object recognition. Thus most of the algorithms will leverage the detection problem on computer vision through some fusion mechanisms as to be shown later. However, there does exist some other research works exploring the possibility to perform object recognition from point cloud data.

In [17], the authors proposed a primary classifier to recognize ground clusters. For each segment, a histogram over all the surface normal vectors' height values was generated, and if the last bin contained the most votes, that segment was classified as ground. This algorithm is not able to differentiate the objects above the ground. Zhang et al. [19] proposed an SVM (Support Vector Machine) based classifier to classify the clusters into ground, vegetation, building, power line, and vehicle. In total 13 features were derived as the input to the SVM classifier. However, this classifier is still very coarse, which is not practical enough for the autonomous vehicle applications.

Lane line making detection- Lane line marking detection is to identify the lane line markings on the road and estimate the vehicle pose with respect to the detected lines. This piece of information can be served as the vehicle position feedback to vehicle control systems. A vast amount of research work has been done in this domain since a few decades ago [20]. However, it is yet to be completely solved and has remained as a challenging problem due to the wide range of uncertainties in real traffic road conditions and road singularities [21], which may include shadows from cars and trees, variation of lighting conditions, worn-out lane markings, and other markings such as directional arrows, warning text, and zebra crossings [22].

As summarized in the survey paper by Hillel et al. in [68], most of the lane line detection algorithms share three common steps: (1) lane line feature extraction, by edge detection [23,24] and color [25,26], by learning algorithms such as SVM [27], or by boost classification [28,29]; (2) fitting the pixels into different models, e.g., straight lines [30,31], parabolas [32,33], hyperbolas [34–36], and even zigzag line [37]; (3) estimating the vehicle pose based on the fitted model. A fourth time integration step may exist before the vehicle pose estimation in order to impose temporal continuity, where the detection result in the current frame is used to guide the next search through filter mechanisms, such as Kalman filter [38] and particle filter [39].

Road Surface Detection- Road surface detection informs the autonomous vehicle on the locations of free space where it can drive without collision. It is the prerequisite for any online path planning and control operations. Generally speaking, the approaches can be divided into three categories: feature/cue based detection, feature/cue based learning, and deep learning.

The feature/cue based detection approaches first identify the feature points or patches in the original image based on some predefined features (e.g., HOG). In the context of stereo images, the feature may refer to the disparity. Based on the identified features, either model fitting or segmentation kind of algorithms will be applied to identify the road surfaces.

On-road object detection- On-road object detection mainly concerns vehicle and pedestrian object classes. Due to the various types, appearances, shapes, and sizes of the objects, those methods reviewed in [40–42] are not robust and not general enough for the application of autonomous vehicles. As listed in the KITTI database, for car, pedestrian, and cyclist detections, all of the leading entries and state of the art methods are based on deep learning schemes. Deep learning has shown its superior performance as compared to conventional learning or feature based approaches in the domain of obstacle detection. Therefore, in this section, we will only review the deep learning based approaches.

Normally, the general pipeline for deep learning approaches is that a set of proposal bounding boxes needs to be generated around the input image, then each proposal box will be sent through the CNN network to determine a classification (including background) and fine tune its bounding box locations as well. The common methods for bounding box proposal are Selective Search [43] and EdgeBoxes [44], which both rely on inexpensive hand-crafted features and economical inference schemes.

Fusion- Different sensors have different strengths and weaknesses. Sensor fusion techniques are required to make full use of the advantages of each sensor. In the context of autonomous vehicle environment perception, LIDAR is able to produce 3D measurements and is not affected by the illumination of the environment, but it offers little information on objects' appearances; conversely, camera is able to provide rich appearance data with much more details on the objects, but its performance is not consistent across different illumination conditions; furthermore, camera does not implicitly provide 3D information.

Following [45], the techniques that have been applied to LIDAR and camera fusion can be roughly divided into two main categories based on their fusion process locations, including fusion at feature level (early stage, centralized fusion) and fusion at decision level (late stage, decentralized fusion). Based on the fusion mechanisms, they can be divided into the following categories: MRF/CRF based, probability based, and deep learning based.

Localization- Localization is the problem of determining the pose of the ego vehicle and measuring its own motion. It is one of the fundamental capabilities that enables autonomous driving. However, it is often difficult and impractical to determine the exact pose (position and orientation) of the vehicle, and therefore the localization problem is often formulated as a pose estimation problem [46].

The problem of estimating the ego vehicle's pose can generally be divided into two sub-problems, namely the pose fixing problem and the dead reckoning problem. In the pose fixing problem, the measurement is related to the pose by an algebraic/transcendental equation. Pose fixing requires the capacity to predict a measurement given a pose, e.g., a map. In the dead reckoning problem, the state is related to the observation by a set of differential equations, and these equations have to be integrated in order to navigate. In this case, sensor measurements may not necessarily be inferable from a given pose. In this sense, pose fixing and dead reckoning complement each other. One of the most popular ways of localizing a vehicle is the fusion of satellite-based navigation systems and inertial navigation systems. Satellite navigation systems, such as GPS and GLONASS, can provide a regular fix on the global position of the vehicle. Their accuracy can vary from a few of tens of meters to a few millimetres depending on the signal strength, and the quality of the equipment used. Inertial navigation systems, which use accelerometer, gyroscope, and signal processing techniques to estimate the attitude of the vehicle, do not require external infrastructure. However, without the addition of other sensors, the initiation of inertial navigation system can be difficult, and the error grows in unbounded fashion over time

PLANNING- Early-stage self-driving vehicles (SDVs) were generally only semi-autonomous in nature, since their designed functionality was typically limited to performing lane following, adaptive cruise control, and some other basic functions [47]. Broader capabilities were notably demonstrated in the 2007 DARPA Urban Challenge (DUC) [48], where it was shown that a more comprehensive planning framework could enable a SDV to handle a wide range of urban driving scenarios. Performance of the SDVs was still far from matching the quality of human drivers and only six of the 35 competition entrants were able to complete the final event, but nevertheless, this milestone demonstrated the feasibility of self-driving in an urban environment [49-52] and revealed important research challenges residing in autonomous driving [53].

Boss, the winning entry of the DUC, Junior, the second place entry, and Odin, the third place entry, along with many others, employed similar three level hierarchical planning frameworks with a mission planner, behavioral planner, and motion planner. While the fourth place entry Talos reportedly used a two level planner with a navigator and a motion planner, the navigator essentially performed the functions of both the mission planner and behavioral planner [54]. The mission planner (or route planner) considers high level objectives, such as assignment of pickup/dropoff tasks and which roads should be taken to achieve the tasks. The behavioral planner (or decision maker) makes ad hoc decisions to properly interact with other agents and follow rules restrictions, and thereby generates local objectives, e.g., change lanes, overtake, or proceed through an intersection. The motion planner (or local planning) generates appropriate paths and/or sets of actions to achieve local objectives, with the most typical objective being to reach a goal region while avoiding obstacle collision. Many recent works since the DUC continue to inherit the same three level hierarchical structure as described here, though the partitioning of the layers are somewhat blurred with variations of the scheme occurring in literature.

CONTROL- The execution competency of an autonomous system, also often referred to as motion control, is the process of converting intentions into actions; its main purpose is to execute the planned intentions by providing necessary inputs to the hardware level that will generate the desired motions. Controllers map the interaction in the real world in terms of forces, and energy, while the cognitive navigation and planning algorithms in an autonomous system are usually concerned with the velocity and position of the vehicle with respect to its environment. Measurements inside the control system can be used to determine how well the system is behaving, and therefore the controller can react to reject disturbances and alter the dynamics of the system to the desired state. Models of the system can be used to describe the desired motion in greater detail, which is essential for satisfactory motion execution.

Classical Control- Feedback control is the most common controller structure found in many applications. Feedback control uses the measured system response and actively compensates for any deviations from the desired behavior. Feedback control can reduce the negative effects of parameter changes, modelling errors, as well as unwanted disturbances. Feedback control can also modify the transient behavior of a system, as well as the effects of measurement noise.

The most common form of classical feedback control is the Proportional-Integral-Derivative (PID) controller. The PID controller is the most widely used controller in the process control industry. The concept of PID control is relatively simple.

However, the use of only feedback terms in a controller may suffer from several limitations. The first significant limitation of a feedback only controller is that it has delayed response to errors, as it only responds to errors as they occur. Purely feedback controllers also suffer from the problem of coupled response, as the response to disturbances, modelling error, and measurement noise are all computed by the same mechanism. It is more logical then to manipulate the response to a reference independently from the response to errors.

Another degree of freedom can be added to the controller by including a feedforward term to the controller. The addition of a feedforward term in the controller can help to overcome the limitations of feedback control. The feedforward term is added to the control signal without considering any measurement of the controlled system. However, the feedforward term may involve the measurement of disturbances, etc. Designing a feedforward control requires a more complete understanding of the physical system, and therefore, oftentimes, a model reference is used for the feedforward controller. The method of combining a feedforward and a feedback term in the controller is also known as two degree of freedom controller.

Motion-predictive control- Autonomous systems need motion models for planning and prediction purposes. Models can also be used in control execution. A control approach which uses system modelling to optimize over a forward time horizon is commonly referred to in the literature as Model Predictive Control (MPC). Model predictive control has been developed to integrate the performance of optimal control and the robustness of robust control. Typically the prediction is performed for a short time horizon called the prediction horizon, where the goal of the model predictive controller is to compute the optimal solution over this prediction horizon. The model, and thus the controller can be changed online to adapt to different conditions. Model predictive control has seen tremendous success in the industrial process control applications, due mainly to its simple concept and its ability to handle complicated process models with input constraints and nonlinearities [55].

Current Research and development issues- Embedded software for control of the vehicle are codes written mainly to control both longitudinal and lateral maneuvers. This control algorithm in both includes a higher level of strategy control and a lower level of vehicle control. The strategy control involves decisions based on information from all vehicles affected by the maneuver and the infrastructure. The lower level vehicle control involves control of vehicle steering, throttle and brake systems.

Longitudinal Control- Four types of information are necessary for longitudinal control: Speed and acceleration of host vehicle, the distance to preceding vehicle, the speed and acceleration of the preceding vehicle and in case of platoon speed and acceleration of the first vehicle. The speed and acceleration of the host vehicle can be measured by speed sensors and accelerometers (On-board OEM vehicle sensors). The distance to preceding vehicle can be measured using range sensors like LIDAR, vision, radar, and ultrasonic. Radar has been the most common range sensor for this case [56]. There are two ways to measure speed and acceleration of the preceding vehicle. One way is to derive it from the host vehicle and the measurement from the range sensors. Another way to obtain the speed and acceleration of the preceding vehicle is by communicating this information between the vehicles [57]. The same method can be used in platooning i.e. the speed and acceleration of the lead (first) vehicle of the platoon is transmitted to vehicles in the platoon. It should be noted that the communication reliability can not be completely trusted [58].

Lateral Control- The strategic level evaluates the environment for lane change maneuver, like the presence of vehicles in the current and adjacent lane and their dynamics. A strategic level model called MOBIL - Minimizing Overall Braking Induced Lane changes, was proposed to deduct lane changing rules for any optional and mandatory lane changes for different car following models [59]. Different lane change trajectories (circular, the cosine approximation to the circular, the polynomial, and the trapezoidal acceleration) were studied, among them trapezoidal acceleration trajectory was the most desirable for best transition time and passenger's comfort [60]. Two different approaches are presented at the vehicle control level [61]. One approach is to treat the maneuvers as a tracking control problem, another approach uses the unified lateral guidance algorithm. In tracking control, a virtual desired trajectory is generated considering the lateral acceleration and jerk using a sliding mode controller. As for unified lateral guidance approach, a yaw rate generator generates the desired yaw rate for a desired maneuvers, either lane change or lane following maneuvers. Commands for steering angle are generated using a reference yaw rate signal and a yaw rate controller for the lane change [62].

CONCLUSION-

Aided by the increase in availability and reduction in cost of both computing power and sensing equipments, autonomous driving technologies have seen rapid progress and maturation in the past couple of decades. This paper has provided a glimpse of the various components that make up an autonomous vehicle software system, and capture some of the currently available state of the art techniques. This paper is by no means a comprehensive survey, as the amount of research and literature in autonomous vehicles has increased significantly in the last decade. However, there are still difficult challenges that have to be solved to not only increase the autonomous driving capabilities of the vehicles, but also to ensure the safety, reliability, and social and legal acceptability aspects of autonomous driving.

Autonomous vehicles are complex systems. It is therefore more pragmatic for researchers to compartmentalize the AV software structure and focus on advancement of individual subsystems as part of the whole, realizing new capabilities through improvements to these separate subsystems. A critical but sometimes overlooked challenge in autonomous system research is the seamless integration of all these components, ensuring that the interaction between different software components are meaningful and valid. Due to overall system complexity, it can also be difficult to guarantee that the sum of local process intentions results in the desired final output of the system. Balancing computational resource allotments amongst the various individual processes in the system is also a key challenge.

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