Artificial Intelligence and Internet of Things for Autonomous Vehicles

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Chapter 2
Artificial Intelligence and Internet of Things for Autonomous Vehicles

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2.1 Introduction

Artificial Intelligence (AI) is a machine intelligence tool providing enormous possibilities for smart industrial revolution. It facilitates gathering relevant data/information, identifying the alternatives, choosing among alternatives, taking some actions, making a decision, reviewing the decision, and predicting smartly. On the other hand, Internet of Things (IoT) is the axiom of industry 4.0 revolution, including a worldwide infrastructure for collecting and processing of the data/information from storage, actuation, sensing, advanced services and communication technologies. The combination of high-speed, resilient, low-latency connectivity, and technologies of AI and IoT will enable the transformation towards fully smart Autonomous Vehicle (AV) that illustrate the complementary between real world and digital knowledge for industry 4.0. The purpose of this book chapter is to examine how the latest approaches in AI and IoT can assist in the search for the AV. It has been shown that human errors are the source of 90% of automotive crashes, and the safest drivers drive ten times better than the average [1]. The automated vehicle safety is significant, and users are requiring 1000 times smaller acceptable risk level. Some of the incredible benefits of AVs are: (1) increasing

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vehicle safety, (2) reduction of accidents, (3) reduction of fuel consumption, (4) releasing of driver time and business opportunities, (5) new potential market opportunities, and (6) reduced emissions and dust particles. However, AVs must use large-scale data/information from their sensors and devices.

The complexity of AV data/information (processing 1 GB per second) is increasing which is used for Advanced Driver Assistance Systems (ADAS) and entertainment. Therefore, it is needed to grow hardware and software requirements, which use sensors, actuators devices and software, to compete the functions similar to the superhuman brain as aimed through AI. AV sensors and devices produce data containing information such as time, date, motion detection, navigation, fuel consumption, voice recognition, vehicle speed with acceleration, deceleration, cumulative mileage, voice search, recommendation engines, eye tracking and driver monitoring, image recognition, sentiment analysis, speech recognition and gesture, and virtual assistance. The total data is thus over a 100 terabyte per year for 100,000 vehicles [2, 3].

This data is predictable to increase further due to the growing adoption of Connected Vehicles (CVs). The ascension of the AV brings new opportunities for industrial manufacturers and dealerships, enabling companies to use AI to increase value for their customers. When it comes to processing this data/information by AI, the most efficient approach is to use Machine Learning (ML) algorithms. The ML algorithms help form behavioural patterns for certain driver profiles and also offer vehicle owners exactly what they need both in the vehicle and through their mobile phones via a corresponding application. They accomplish this by remembering their behaviour and analysing their driving history and the situation on the road.

Although AI can handle the AV big data, some of the extra data conditions, such as traffic, pedestrians, and experiences, will need to be collected through various IoT networks, such as Local Area Network (LAN), Wide Area Network (WAN), Wireless Sensor Network (WSN), and Personal Area Network (PAN). This huge data/information needs to have some substances, such as embedded electronics devices, sensors, vehicles, buildings, software, and network connectivity, that enable them to collect and share the data. These IoT-enabled AVs utilize a number of integrated devices to provide many real-time assistance such as improving safety, reduction of fuel consumption, and security for a vehicle. Both IoT and automotive industry 4.0 will be transformed to provide a big boost through reducing machine failure, improving quality control, increasing productivity, and lowering costs at the same time. The potential and the predictions of IoT technology is astonishing. A report by Morgan Stanley Research [4] shows that at least nine industrial manufacturers will benefit from AVs through providing a number of superior technology, key features, and services:

(1) Original Equipment Manufacturers (OEM), (2) Auto dealers, (3) Autonomous trucks, (4) Chemical engineering, (5) Electric utilities, (6) Semiconductor, (7) IT hardware-software, (8) Telecom and communications, and (9) Beverage and restaurant sectors.

This chapter observes the technical trend towards AV with some discussion about key issues and challenges faced by the automotive industry and Sect. 2.2 explains the AI field in detail with their approaches. In Sect. 2.3, the AV is described with challenges and opportunities. In Sect. 2.4, the IoT network including cloud and edge computing is demonstrated that allows us to use the generated huge amounts of data from networked and connected devices. Finally, the combination of AI approaches and IoT for AVs is concluded.

2.2 Artificial Intelligence (AI) Approaches

AI is a field of computer science and engineering used for different smart applications aiming to make intelligent machines. AI works and responds like humans, intelligently and independently through learning from experience and adjusting to new participations.

2.2.1 Introduction to Artificial Intelligence: Benefits and Challenges

The trend of industrial revolution such as technologies, automation, and data exchange is shown in Fig. 2.1. Current industries have new challenges in terms of competition and market demand and they must take radical change to Industry 4.0 evolution. Artificial Intelligence (AI) is one of the capabilities that enables

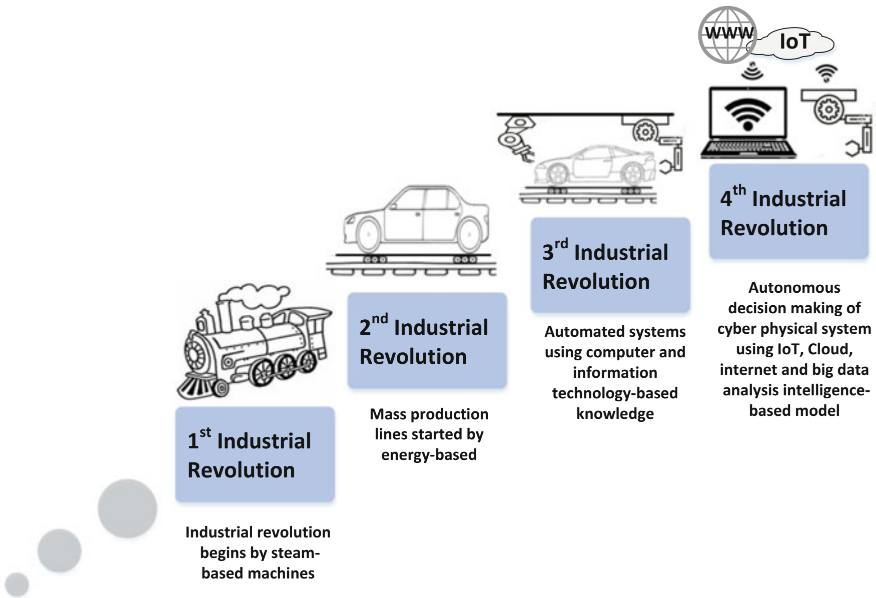


Fig. 2.1 The fourth industrial revolution

improved decision dynamics and better decision precision for industry 4.0, resulting in better business performance, reducing machine failure, improving quality control, increasing productivity, and lowering costs. AI has a number of benefits including: (1) using data to automate learning, (2) enhancing the intelligence abilities to current products, (3) adapting intelligent learning algorithms to do the programming by the data, (4) analysing rationally of data, and (5) improving data accuracy [5]. Although AI most likely changes today's world, it has its own limitations. The biggest challenges of AI are about learning from the experience, and there is no way that the knowledge can be incorporated in the learning. Besides that, any inaccuracies in the data will be reflected in the results and are very challenging.

2.2.2 Artificial Intelligence: History and Approaches

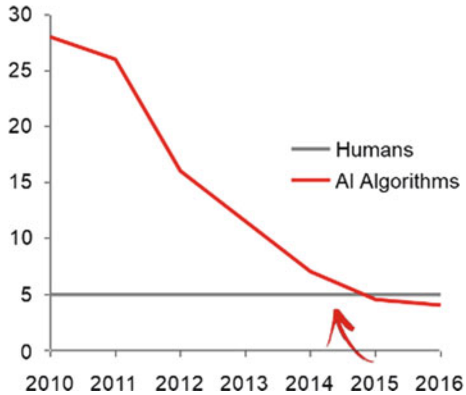
AI is based on combining large amounts of data. It processes the data very fast with iterative processing through the intelligent algorithms, which allow the software to learn from features or patterns of the data. AI has become more widespread since recently it substantially decreased the vision error (less than 5%) in comparison with human vision error as shown in Fig. 2.2 [6, 7].

The history of AI began in antiquity, but it was introduced by John McCarthy in 1950s. A brief evolution of AI is schematically shown in Fig. 2.3 [8]

AI was invented in three main areas: (1) Neural Networks (NNs) from 1950s to 1970s that were mainly focused based on stirs excitement for 'thinking machines', (2) Machine Learning (ML) from 1980s to 2010s that became popular approaches of AI, and (3) Deep Learning (DL) at the present decade that drives the breakthroughs. Our schematic diagram of AI approaches is shown in Fig. 2.4. As can be seen, in general, AI can be divided into three main fields: symbolic learning, statistical learning, and machine learning. These and briefly explained as follows:

Symbolic Learning: Symbolic learning is based on human readable symbols of logic, problems, search and the symbolic learning rules, which are created

Fig. 2.2 The vision error rate (%) from human and AI algorithm [7]



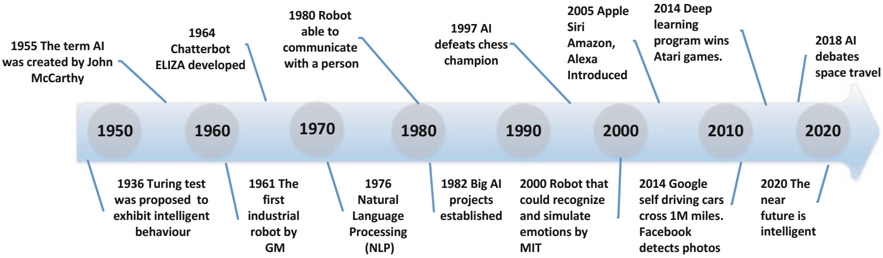


Fig. 2.3 A schematic evolutionary diagram of Artificial Intelligence (AI)

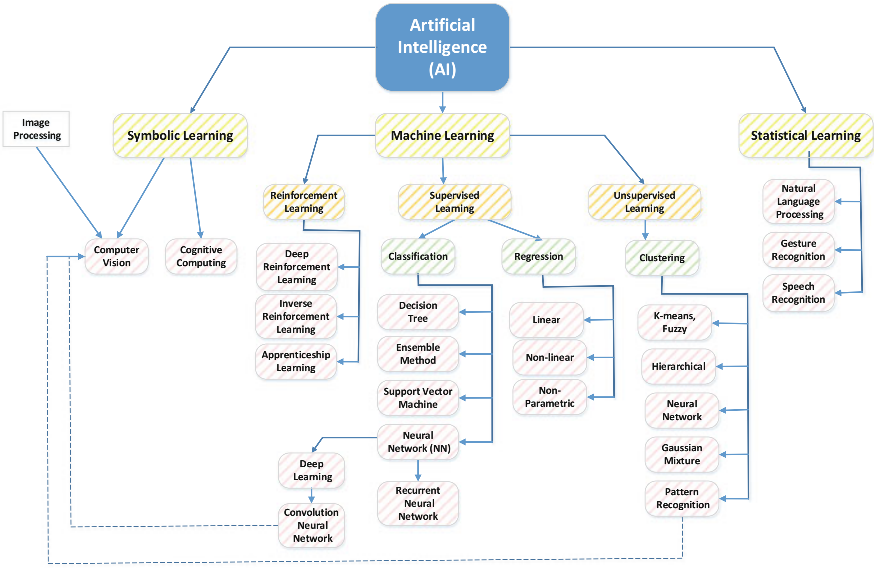


Fig. 2.4 Artificial intelligence approaches/apparatuses

through human intervention. Mixtures of symbols with their interrelations is called reasoning. In order to construct a symbolic reasoning, humans start to learn the rules of the phenomena relationships, and then the code of those relationships transfer into a program. Symbolic learning can be divided into cognitive computing and computer vision.

Statistical Learning: Statistical learning is mathematics intensive and deals with the problem of finding a predictive function based on data. It involves forming a hypothesis before proceeding to building a model. Statistical learning relies on rule-based programming and is formalized in the form of relationship between variables. Statistical learning is also based on a smaller dataset with some attributes, operates on assumptions, such as normality, no multi-collinearity, and homoscedasticity.

Machine Learning: Machine Learning (ML) creates and automates analytical/numerical models and algorithms that can be used to improve the system performance in a specific task. ML uses approaches from heuristic methods, operations research, and statistics, and finds hidden insights in data without explicitly being planned where to look or what to accomplish. The major ML subfields are unsupervised, supervised, and reinforcement learning, which are explained as follows:

Unsupervised Learning: Unsupervised learning is a group of understanding data created based only on input data. One of the unsupervised learning techniques is clustering that involves the grouping of data points through a set of data points. The clustering algorithm can classify each set of data points into a cluster group (see Fig. 2.5a).

Supervised Learning: Supervised Learning (SL) develops a model to predict based on input and output data. SL approaches can be divided into: (1) *Regression* that is an approach to find the relationship between variables. In machine learning, this is used to predict the outcome of an event based on the relationship between variables obtained from the dataset (see Fig. 2.5b). (2) *Classification* that is trying to identify to which of a set of categories for a new observation belongs accurately and it also attempts to predict the target class for each category of the data (see Fig. 2.5c).

Reinforcement Learning: Reinforcement Learning (RL) is a new AI technology based on decision-making that will help AI to advance extremely into the area of machine learning of the real world. A brief comparison of unsupervised, supervised, and reinforcement learning are listed in Table 2.1.

RL uses an agent that learns interactively with the environment through trial-and-error response from its experiences and own actions. Fig. 2.6 shows a simple (RL) framework that can solve the decision problem by using a sequential decision problem through interactive to measure of the feedback performance [9]. In general, RL tries to find a decent mapping that defines perceptions to do any actions for

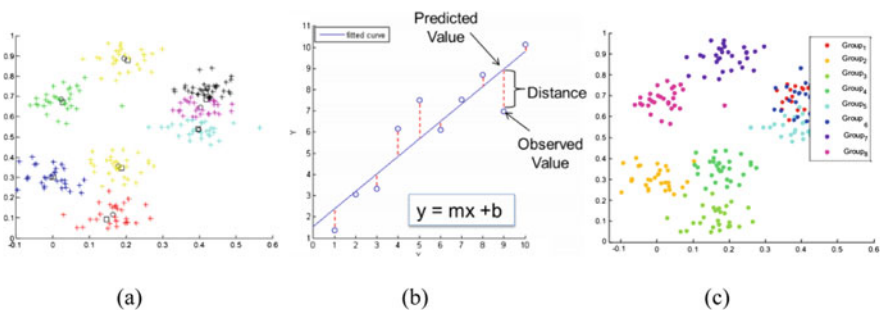


Fig. 2.5 A sample unsupervised and supervised learning methods: (**a**) clustering, (**b**) regression, and (**c**) classification

Table 2.1 Comparison methods of machine learning

	Unsupervised learning	Supervised learning	Reinforcement learning
Model affection	Model does not affect the input data	Model does not affect the input data	Agent can affect its own observations
Learning structure	Learning underlying data structure	Learning to approximate reference answers	Learning optimal strategy by trial and error
Feedback	No feedback required	Needs correct answers	Needs feedback on agent's own actions

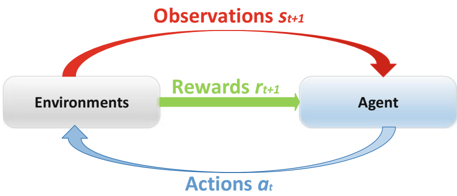


Fig. 2.6 A simple reinforcement learning framework

addressing situations for the decision-maker cooperating with an environment. RL is a powerful method to speed up initial learning with remarkable results [10, 11] that has become popular within the community of computer science, automation, control, and mechatronics, and recent years have perceived to widely use especially to solve the multi-agent problems.

The RL can be mathematically formulated as follows. The environment is a current state s out of a set S, and the agent action is a subset of an action set A, where S: $S \times A \rightarrow S$ and R: $S \times A \rightarrow \mathbb{R}$, action a in state s, the state $S(s, a)$, a reward $R(s, a)$.

The goal function is to learn a policy function p: $S \rightarrow A$, by choosing actions that maximize expected future rewards. This is typically done by defining a discount factor $\gamma \in [0, 1)$, used to scale future rewards in the total value of a policy:

$$V^p(s) = \sum_{k=1}^{+\infty} \gamma^{k-1} r^k = r_1 + \gamma r_2 + \gamma^2 r_3 + \cdots \tag{2.1}$$

where rk is the reward obtained after k steps, starting from state s and following policy p thereafter.

2.2.3 *State of the Art of Artificial Intelligence Approaches*

One of the new powerful and flexible machine learning that represents the world with hierarchy of implications with more abstract representations is Deep Learning (DL).

Deep Learning

In most of machine learning techniques, in order to reduce the complexity of the data and make patterns more visible to learning algorithms to work, the applied features need to be identified by a domain expert. The main gain of Deep Learning (DL) algorithms are to learn in high-level features from data in an incremental way [12]. DL is based on conception, perception, and decision-making. It uses huge neural network layers by using many processing units that has many advantages of advances to improve training techniques for learning complex patterns in lots of data. Common complex engineering applications include activity recognition, video labelling, image, speech recognition, object recognition, and several types. DL is also transmitting significant inputs to other areas of perception, such as audio, speech, and natural language processing.

Deep Reinforcement Learning

Although AI has many successful approaches, the essential technology of AI is the combination of deep learning and Reinforcement Learning (RL) which produce inspiring results in learning. Deep RL approach extends reinforcement learning by using a deep neural network and without explicitly designing the state space [13, 14]. Thus, Deep RL refers to goal-oriented algorithms to open up many new applications in areas such as engineering, and many more.

2.3 Autonomous Vehicle

2.3.1 Introduction

An Autonomous Vehicle (AV) is a vehicle that can guide itself, as opposed to being controlled by human. The AV is a kind of driverless vehicle that has become in reality and is the art of driving using computers for future. AVs have been targeted due to: (1) increasing vehicle safety, (2) reduction of accidents, (3) reduction of fuel consumption, (4) releasing of driver time and business opportunities, (5) new potential market opportunities, and (6) reduced emissions and dust particles. It is planned that around ten million AVs will be on to the roads by 2020 and is expected that AVs produce $7 trillion annual revenue stream by 2050 [15].

2.3.2 Automated Vehicle: Levels and History

Vehicles have six levels for Advanced Driver Assistance Systems (ADASs) for automated vehicles. The journey level of automation to fully autonomous vehicle as shown in Fig. 2.7 are: Level zero—no automation and the human executes

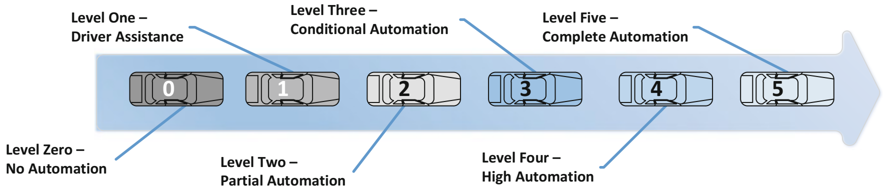


Fig. 2.7 The journey of automation to fully autonomous vehicle

to operate all the dynamic driving tasks like accelerating or slowing down, steering, braking, and so forth. Level one—driver assistance by system of either acceleration/deceleration or steering using information about driving conditions. Level two—partial automation of vehicle which combined automated functions both acceleration/deceleration and steering. Level three—conditional automation of the driving mode that is precise performance by an automated driving system when the driver response to request. Level four—high automation is the vehicle capable of performing all driving functions under certain conditions even if a human driver does not reply to a request. Level five—complete automation is the vehicle accomplished to perform all driving jobs/functions under all conditions [16].

In level four and five, AVs are capable of performing all driving functions by conjunction of many systems and sensors with each other to control a driverless car. Table 2.2 listed the six levels of automated vehicle including the ADAS technologies, sensors, and actuators (detailed in section "AV Objective Sensors") which have been constructed so far [16].

The idea of Autonomous Vehicles (AVs) is started from 1930s when science fiction writers visualized and innovated the self-driving cars as a new challenge for automotive industries. A brief history of autonomous driving is listed in Table 2.3.

In the near future, AV will reach fantastic human performance for competences compulsory for driving by using the sensing algorithms. Intelligent perception is close to do human tasks such as recognition, localization, path tracking, and tracking for the AV. A new report predicts AVs will be widely adopted by 2020 and the adoption of AV competences won't be restricted to individual transportation [17]. As of 2016, many countries such as the USA (Nevada, Florida, California, and Michigan states), Canada, France, the United Kingdom, and Switzerland have approved some laws and regulations for the testing of AVs on public roads.

2.3.3 Autonomous Vehicle: Key Issues and Complexities

In general, Autonomous Vehicle (AV) needs autonomous mobile navigation to find its: (1) localization, (2) map building, (3) path planning, and (4) path tracking. In addition, it is required the AV obstacle avoidance through detection and classification.

Table 2.2 The six levels of automated vehicle including the ADAS technologies, sensors, and actuators [16]

Level 5	Fully autonomous driving											
Level 4	Automated route (trained)						Automated route (destination)					
Level 3	Automated highway driving			Automated city driving			Automated valet parking			Evasive manoeuvres		
Level 2	AEB-city			AEB-urban		AEB pedestrian/ cyclist		Intersection assist		Overtaking assist		
Level 1	Acc Stop and Go	Lane keep		Cross-traffic assist		Real-collision mitigation		Auto parking assist		Navigation		Electric horizon
		Assist										
Level 0	Anti-Lock	Stability	Cruise	Electric power steering	Blind spot morning	Pedestrian/ cyclist		Parking assist	Traffic sign	Lane departure warning	Forward collision warning	Surround/rear view
	Brakes	Control	Control			Detection			Recognition			
Sensors/ actuators	Propulsion controls	Steering	Brake					Inertial	Ultrasonic			Driver
		Controls	Controls	Radar	Cameras	LiDAR	GPS	Sensors	Sensors	MAPS	V2X	Monitoring

Table 2.3 A brief history of autonomous driving by various research and development projects

Year	Companies/projects	Activity
1925	Houdina Radio Control	Demonstrates a radio-controlled ‘driverless’ car
1939	General Motors	Exhibit ‘Futurama’ model
1949	RCA	Begin the technical explorations
1950s	General Motors /RCA	Research collaborative a large project
1950s	General Motors	The concept car called Firebird II
1956	General Motors	The Firebird II exhibited is equipped with receivers for detector circuits in roadways
1958	Chrysler	The first car with cruise control called imperial
1960s	Kikuchi and Matsumoto	Wire following in Japan
1964	General Motors	Futurama II exhibit
1964	OSU	Research by Fenton
1970s	Tsugawa	Vision guidance in Japan
1979	Stanford Cart	Used a video processing to navigate a cluttered room without human input
1980s	Dickmanns	Vision guidance in Germany
1986	California PATH and PROMETHEUS	Programs start
1994	PROMETHEUS	Demo in Paris
1995	VaMP	Autonomous vehicle drivers (almost) completely autonomously for 2000 km
1995–1998	National AHS Consortium	Demo ‘97
2003	PATH	Automated bus and truck demos
2004–2007	DARPA	Grand challenges is founded to incentivise autonomous vehicle development
2009	Google	Self-driving car project begins
2015	Tesla	Release its Autopilot software update
2016	Google	Self-driving car has its accident
2017	General Motors	Plans to include autonomous controls in the Bolt and Super cruise in Cadullic Ct6
2017	Volvo	Plans to launch 100 self-driving vehicles to customers

Some of mobility key issues of AVs are: (**1**) **Software accuracy** and fail proof software is needed to make sure no problems will happen, (**2**) **Map completeness and correctness** through improved features on maps with some additional details such as identifying the surrounding objects and generating some virtual maps to assist the AVs in finding the correct way and looking at dynamic obstacles (pedestrians and vehicles), (**3**) **Sensor fusion and estimation** to sense diverse unpredicted conditions to calibration be able to distinguish between very dangerous situations from those less dangerous are needed.

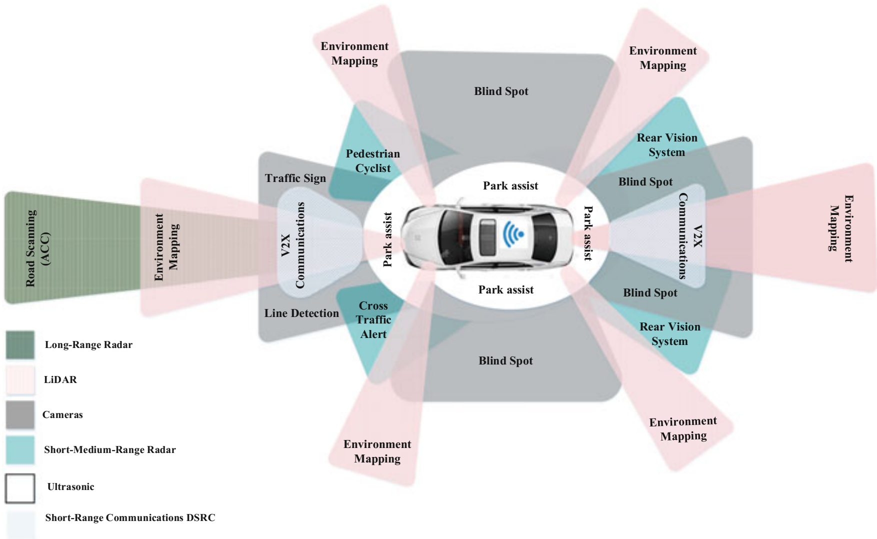


Fig. 2.8 The complexity situation awareness of autonomous vehicle caused by using multi-sensors

The sensors, awareness area, architecture, and software of AVs become quite complex due to the difficulty of the tasks. Among the above AVs issues, currently sensors cannot process quickly to distinguish dangerous situations. A variety of sensors and devices are required in order to keep the vehicle on path and avoid obstacles. The huge information then generate the situational awareness of the vehicle and its surroundings and make appropriate decisions while driving (Fig. 2.8). The combination of sensors with different situational awareness, failures, and real-time response shows the AVs complexities that they need to have a comprehensive software. One approach to reduce complexity of AVs is logical development of actions. Additional approach is to minimize the amount of state information and the duration of the retaining of information. A limited inputs data to the AV system make its behaviour more deterministic. Nonetheless, the main difficulty to reduce data is that the vehicle has limited ability to navigate and manoeuvre. Therefore, there are many AV challenges to be considered and can be solved through a design of AV system architecture and software.

AV Objective Sensors

The AV objective sensors are:

Ultrasonic: The sensor uses sound waves with high-frequency that bounce back to measure the objective distance of a vehicle. It releases sound waves (50 kHz) and listens for bounce back. Then it calculates to determine range based on time-of-flight.

Cameras: Cameras detect the real-time obstacle to enable lane departure and track roadway information (similar to road signs). An image created from camera includes a huge array of values of individual pixels taken individually; these numbers are almost worthless. The image must be understand by conversion of low level information image information into high-level image information by using computer vision algorithms. Computer vision includes analysis of signals from: (a) thermal sensors, (b) cameras, (c) laser range finders, (d) X-ray detectors. Computer vision has three components: (1)Segmentation is where the physical objects are, (2) Classification is what these objects are, and (3) 3D reconstruction is estimating ranges from 2D pictures.

Radar: The sensor releases radio waves that detect short- and long-range depth. Radar sensors dotted around the vehicle monitor the position of vehicles nearby. The radar emits a radio signal (green) which is scattered in all directions (blue). The time-of-flight t for the signal returns the signal to the radar and gives the distance d.

LiDAR: This sensor measures the distance by target brightness with pulsed laser light and measures reflected pulses with sensors to create 3D map of area. LiDAR sensors help to detect the boundaries of roads and identify lane markings by active pulses of light off the vehicle's environments.

DSRC: Dedicated Short-Range Communications (DSRC) is one-way or two-way short-range to medium-range wireless communication channels precisely designed for vehicle use and a consistent set of standards and protocols. DSRC can use as 4G, Wi-Fi, Bluetooth, etc. to Vehicle to Infrastructure (V2I) communication, Vehicle-to-Vehicle (V2V), and Vehicle-to-everything X (V2X). The suitable device is to have lowest latency.

AV Pose Sensors

A vehicle has (at least) six degrees of freedom stated by the pose: $(x, y, z, \varphi, \theta, \psi)$ shown in Fig. 2.9 and AV needs to have some sensors,

Where position $= (x, y, z)$ and attitude: roll is the angle between y' and the x–y plane, $-\pi < \varphi < \pi$, which is the angle between x' and the x–y plane $-\pi < \theta < \pi$, and

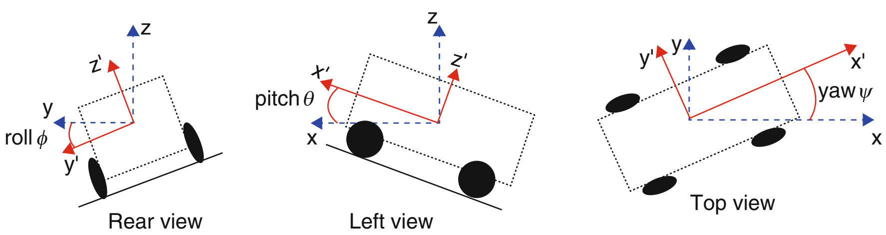


Fig. 2.9 Six degrees of freedom of vehicle dynamics

yaw is the angle between x and the projection of x' on the x–y plane. $-\pi < \psi < \pi$ as shown in Fig. 2.9.

GPS: Triangulates position for a moving receiver: latitude, longitude, altitude, and also speed and direction of movement can be estimated position of vehicle using satellites. Current GPS technology is limited to a certain distance.

Wheel Odometry: It computes changes in the 2D-pose (x, y, θ) from vehicle steering angle and velocity (steering angle from angle sensor and velocity from shaft encoders or speed sensor), it also translates steering angle and velocity to kinematics equations (x, y, θ).

Accelerometers: A variant for measuring change in position (x, y, z) and force F.

Gyroscopes: Measures rotation with one, two, or three degrees of freedom. It estimates (φ, θ, ψ) by summing up gyroscope rotations.

The foremost above AV issues is sensor fusion, as AV needs to have multi-various homogeneous as well as heterogeneous sensors for detection and identification of AV's objectives which are compulsory to design AVs.

Vehicle Dynamics: While pose sensors to be developed rely only on the kinematics of vehicle motion, a dynamic model is required for validating the vehicle performance. The lateral dynamics of a vehicle in the horizontal plane are represented here by the single track, or bicycle model with states of lateral velocity, u_y, and yaw rate, r. The bicycle model (see in Fig. 2.10) is a standard representation in the area of ground vehicle dynamics and has been used extensively in [18, 19]. While detailed derivation and explanation can be found in many textbooks [20, 21], the underlying assumptions are that the slip angles on the inside and outside wheels are approximately the same and the effect of the vehicle roll is small.

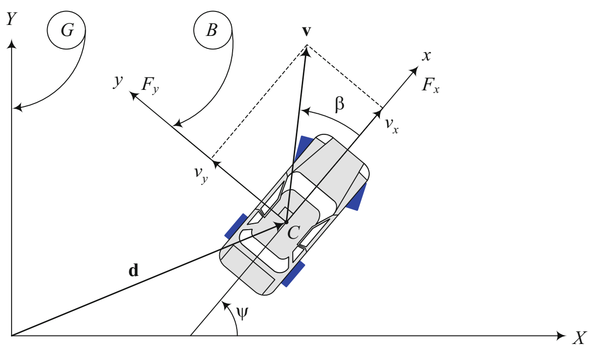


Fig. 2.10 Bicycle model [21]

Data Fusion

As mentioned in the above section, the local situational awareness of Autonomous Vehicle (AV) mostly depends on extracting information from a variety of sensors (e.g. camera, LiDAR, Radar) each of which has its own operating conditions (e.g. lighting, range, power). One of the open issues in the reconstruction and understanding of the environment of AV is how to fuse locally sensed data to support a specific decision task such as vehicle detection [22]. Sensor fusion is a software for combining data from multi-sensors for the determination of improving system performance. The accuracy independent vehicle position and orientation of combining data from the separated sensors will be calculated [23].

Data fusion techniques can be categorized into the following methods:

- Estimation: The method optimally performs the estimation task by using a well-defined statistical framework [24] such as: (1) Weighted Averaging (WA) and (2) Kalman Filtering (DF) [25].
- Classification: It can be used in order to solve classification problems. The challenge is to partition a multi-dimensional feature space into distinct regions where each represents a specific class (group) such as: (1) Density Estimation (DE), (2) K-Nearest Neighbour, (3) Discriminant Analysis (DA), (4) Support Vector Machines (SVM), (5) Decision Trees (DT)[26].
- Inference: This method sets up a further category of fusion techniques based on probability theory such as: (1) Naive Bayesian Inference (NBI), (2) Dempster-Shafer Evidential Reasoning (DSER) [26].
- Artificial intelligence: These approaches are based on heuristic methods such as: (1) Fuzzy logic (FL), (2) Artificial Neural Networks (ANN)[27].

Table 2.4 provides[28] a coarse overview of the advantages and disadvantages of the selected algorithms concerning the applicability to embedded real-time processing.

2.3.4 Recent Autonomous Vehicle Developments

Current vehicles use a wide variety of sensing competences. Moderately, these days a vehicle has seventy sensors including ambient light sensors, accelerometers, gyroscopes, and moisture sensors in the USA [29]. Vehicle sensors are not new components and they were constructed before 2000; the sensors were used for the internal state of the vehicle such as its wheel position, acceleration, and speed. Vehicles already had a number of functionalities such as Anti-lock Braking Systems (ABS), Airbag Control (AC), Traction Control Systems (TCS), and Electronic Stability Control (ESC) for combining real-time sensing with perception and decision-making. The recent commercialized automated competences functions are listed in Table 2.5.

Table 2.4 Overview of advantages and disadvantages of selected algorithms of fusion data [28]

Methods	Advantages	Disadvantages
K-Nearest Neighbour (KNN)	Notable classification results No (re)training phase Distance metrics Error probability bounded	Time consuming Classification time Memory utilization Finding optimal *k* no online learning
Mahalanobis Distance Classifier (MDC)	Notable classification results Approximative online learning	Estimation of statistics Complex matrix ops
Linear Discriminant Analysis (LDA)	Linear decision boundary Fast classification Fast parameter estimation online learning	Gaussian assumptions Training time Complex matrix ops
Quadratic Discriminant Analysis (QDA)	Quadratic decision boundary Fast classification Fast parameter estimation Online learning	Gaussian assumptions Training time Complex matrix ops
Naive Bayes Classifiers (NBC)	Fast execution ability Fast classification Online learning	Gaussian assumptions
Artificial Neural Networks (ANN)	Fast execution ability Fast classification Arbitrary decision boundaries Online learning	Training time Use of heuristics
SVM	Fast execution ability Fast classification Online learning	Training time Limited decision boundaries

Table 2.5 Recent AV automated functions [29]

Context	Automated functionality	Date
Parking	Intelligent Parking Assist System	Since 2003
Parking	Summon Since	2016
Arterial & Highway	Lane departure system	Since 2004 in North America
Arterial & Highway	Adaptive cruise control	Since 2005 in North America
Highway	Blind spot monitoring	2007
Highway	Lane changing	2015

The automated functionalities help drivers or totally take over well-defined actions for increased comfortability and safety. Current vehicles can perform adaptive cruise control on highways, park themselves, alert drivers about objects in blind spots during lane changes and steer themselves during stop-and-go traffic. Vision and radar technology are used to avoid collision by autonomously brake when risk of a collision is detected for vehicles. By using deep learning, vehicles are able to detect objects in the environment and recognize sound [29].

The automotive industry aimed to continuously develop Autonomous Vehicle (AV) in the last few years [30]. Around 46 private companies work in auto tech on Autonomous Vehicle (AV). A report by Gartner shows that it is expected that by 2020 around 250 million vehicles will be connected with each vehicle, Vehicle to Everything (V2X) or Vehicle to Infrastructure (V2I) systems [30]. Therefore, vehicles will be able to capture and share not only vehicle's situations and location data but also the road conditions (such as weather, traffic congestion and accidents, road geometry, wind...), completely in real time. Although AVs are equipped with sensors and cameras, but the communication systems enable the AVs to generate enormous amounts of data and information. Some of the recent vehicle hardware and software developments are briefly given as follows [31]:

1. Keolis and NAVYA (2017), in partnership with the city of Las Vegas, launched the first autonomous, fully electric shuttle to be deployed on a public roadway in the United States (2017).
2. Toyota (2018) announces 'e-Palette' concept vehicle which is a fully electric autonomous vehicle that can be customized by a partner for applications such as food deliveries (Pizza Hut), ride-sharing (Uber), or store fronts (Amazon).
3. Udelv (2018), a Bay Area tech company, completed the first delivery of goods by a self-driving car when it delivered groceries in San Mateo.
4. Hyundai (2018) announced that a fleet of its fuel cell electric cars made a fully successful automated trip from Seoul to Pyeongchang. This is the first time a Level 4 car has been operated with fuel cell electric cars.

2.3.5 Artificial Intelligence in Autonomous Vehicle

An Artificial Intelligence (AI) model for Autonomous Vehicle (AV) includes three steps: (1) data collection, (2) path planning, (3) act as illustrated in Fig. 2.11.

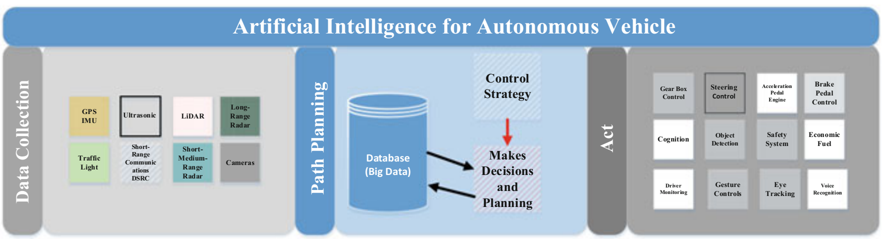


Fig. 2.11 An artificial intelligence model for autonomous vehicle including data collection, planning, and act

Step 1: Data Collection

AVs are equipped with multi-sensors and devices such as radars, cameras, and communication to produce a huge data from its vehicle and environment. These AVs data include the road, road infrastructure, other vehicles and every other object on/near the road, parking, traffic information, transport and environmental information just similar to a human driver. These data are then will be sent to be processed as AV updated information. This is the first AV communication with specific vehicle situations and environment conditions.

Step 2: Path Planning

The huge data from AV system will store and add with pervious driving experiences from every ride in a database called Big Data. Also, an AI agent acts on the Big Data to make meaningful decisions through strategy control. The control strategy of path planning for AVs enables self-driving vehicles to find the safest, most convenient, and most economically beneficial routes from point A to point B by using the pervious driving experiences which help the AI agent make much more accurate decisions in the future. Finding routes is complicated by all the static and manoeuvrable obstacles that a vehicle must identify and bypass. Path planning control strategy involves finding a geometric path from an initial configuration to a given configuration so that each configuration and state on the path is feasible (if time is considered). Path planning control strategy is involved with *Manoeuvre* planning which aims at taking the best high-level decision for a vehicle while considering the path specified by path planning mechanisms and *Trajectory* planning which is the real-time planning of a vehicle's move from one feasible state to the next, satisfying the vehicle's kinematic limits based on its vehicle dynamics and as constrained by the navigation mode. The AV knows exactly what to do in this driving environment and/or driving situation.

Step 3: Act

Based on the decisions made by the AI agent, the AV is able to detect objects on the road, manoeuvre through the traffic, parking spot, obstacles, entertainment, traffic lights, bicycle, pedestrians, working areas, weather conditions, and other vehicles without human driver interposition and goes to the destination safely. AVs are also being equipped with AI-based control and functional systems such as steering control, acceleration by pedal engine, voice and speech recognition, brake pedal control, eye tracking, safety system, gesture controls, economic fuel, and other driving assistance/monitoring systems. These AV process loop including data collection, path planning, and act will take place repetitively. The more the number of data loop takes place, the more intelligent the AI agent becomes, resulting in a higher accuracy of making decisions, especially in complex driving situations.

2.3.6 Recent Autonomous Vehicle Challenges

Though today, Autonomous Vehicles (AVs) have become a reality after many years of research and development, but still, there are a huge mountainous challenges in completely designing autonomous system for the AVs such as: engineering technologies, regulatory, lack of industry standardized technology and tools, consumer trust and acceptance, to name a few. At each progressive level of autonomy, the challenges become more difficult. But, among of the challenges, still engineering technologies especially in Perception, Localization, Planning, Control, and Prediction (PLPCP) of data/information for following conditions/areas are required to be improved [32]:

Road Conditions: Road conditions are extremely changeable and vary uncertain from point to point. In some areas, there are smooth and marked broad highways. But in some other areas, road conditions are highly deteriorated—no lane marking. Lanes are not defined, there are potholes, mountainous and tunnel roads where external signals for direction are not very clear and likewise.

Weather Conditions: Weather conditions play another spoilsport. There could be a sunny and clear weather or rainy and stormy weather. AVs should work in all sorts of weather conditions. There is absolutely no scope for failure or downtime.

Traffic Conditions: AVs would have to get onto the road where they would have to drive in all sorts of traffic conditions. They would have to drive with other AVs on the road, and at the same time, there would also be a lot of humans. Wherever humans are involved, there a lot of emotions are involved. Traffic could be highly moderated and self-regulated. But often there are cases where people may be breaking traffic rules. An object may turn up in unexpected conditions. In the case of dense traffic, even the movement of few centimetres per minute does matter. One can't wait endlessly for traffic to automatically clear and have some precondition to start moving. If more of such cars on the road are waiting for traffic to get cleared, ultimately that may result in a traffic deadlock.

Accident Liability: The most important aspect of AVs is liability for accidents. Who is liable for accidents caused by an AV? In the case of AVs, the software will be the main component that will drive the vehicle and will make all the important decisions. While the initial designs have a person physically placed behind the steering wheel, newer designs showcased by Google, do not have a dashboard and a steering wheel. In such designs, where the car does not have any control like a steering wheel, a brake pedal, an accelerator pedal, how is the person in the vehicle supposed to control the vehicle in case of an untoward incident? Additionally, due to the nature of AVs, the occupants will mostly be in a relaxed state and may not be paying close attention to the traffic conditions. In situations where their attention is needed, by the time they need to act, it may be too late to avert the situation.

Radar Interference: AVs use lasers and radar for navigation. The lasers are mounted on roof top while the sensors are mounted on the body of the vehicle. The principle of radar works by detecting reflections of radio waves from surrounding objects. When on the road, a vehicle will continuously emit radio frequency waves, which get reflected from the surrounding vehicles and other objects near the road. The time taken for the reflection is measured to calculate the distance between the vehicle and the object. Appropriate action is then taken based on the radar readings. When this technology is used for hundreds of vehicles on the road, will a vehicle be able to distinguish between its own (reflected) signal and the signal (reflected or transmitted) from another vehicle? Even if multiple radio frequencies are available for radar, this frequency range is unlikely to be insufficient for all the vehicles manufactured.

Big Data Analytics: It is required that both training systems and real-time decision-making of AV volumes of data are deployed. Without efficient data management, the sheer resources the process will consume can dramatically slow down innovation. Explore the four data considerations in the AV: (1) data acquisition, (2) data storage, (3) data management, and (4) data labelling. For those early in the data collection process, consideration of one's data approach and thoughtful decision-making regarding relevant tradeoffs will help ensure an action plan that is both executable and expeditious. For those where data collection is becoming increasingly precarious, a careful retrofit that leverages what is already in place can take the organization to a more secure, accessible, and sustainable data approach.

A review of the six intelligent approaches: Representation Learning, Deep Learning, Distributed and Parallel Learning, Transfer Learning, Active Learning, and Kernel-Based Learning for applying scalable machine learning solutions to big data are presented and remarked in detail in this book [33].

Vehicular Communication: In order to resolve PLPCP, AVs need to have a network platform through the Internet communication with a huge data/information for staging and deploying of: (1) vehicle side: vehicle diagnostics data, vehicle real-time location, acceleration, speed, fuel consumption and emissions, and (2) environment side: real-time traffic information, traffic signal messages, safety messages, eco-routes, eco-speed limits, parking information, etc., and (3) energy efficiency powertrain side: hybrids, electric vehicles, and other alternative power sources.

2.4 Internet of Things

2.4.1 Introduction

The technical term Internet of Things (IoT) has been suggested by Kevin Ashton in 1999 [34]. The meaning of 'Things' has changed as technology evolved in last decade, but the main goal which is a digital device can make sense of information without the human intervention remains the same. The Internet made the interconnection between people possible at an unprecedented scale and pace. The next wave of connectivity is coming much faster to interconnect objects and create a smart environment. There are currently nine billion interconnected devices, more than the number of people in the world and it is expected to reach 24 billion devices by 2020. The main advantage of such a massive number of connected devices is accessing to big datasets which can be utilized in smart applications [35]. Several industries including agriculture, mining, manufacturing, and automotives have already adopted this technology to improve the efficiency and control of their processes. In this section, we will introduce the utilization of IoT technologies in automotive industry which is mainly used for autonomous vehicles.

Autonomous Vehicles (AVs) must have a number of abilities for generation, collection, analysis, processing, and storage of vehicular data from various sources road conditions such as traffic congestion and accidents through a communication network. The Internet of Things (IoT) is an emerging technology which includes a network of physical objects such as: buildings and other items, vehicles, embedded with hardware devices, software, sensors, and network connectivity that enables these substances to collect and exchange data to information without human interaction [34]. The concept of IoT is evolving from Machine-to-Machine (M2M) connectivity as shown in Fig. 2.12. M2M connects isolated systems of sensors to servers with no (or little) human intervention, whereas IoT takes machine-to-machine connectivity, integrates web applications, and connects it to cloud computing systems. Adoption of IoT in AVs has several technical benefits including the capability to monitor vehicles to improve fleet efficiency, safety factors, reduce the vehicle crash, vehicle usage, and provide more responsive service to customers, more drivers interact with the environment around them.

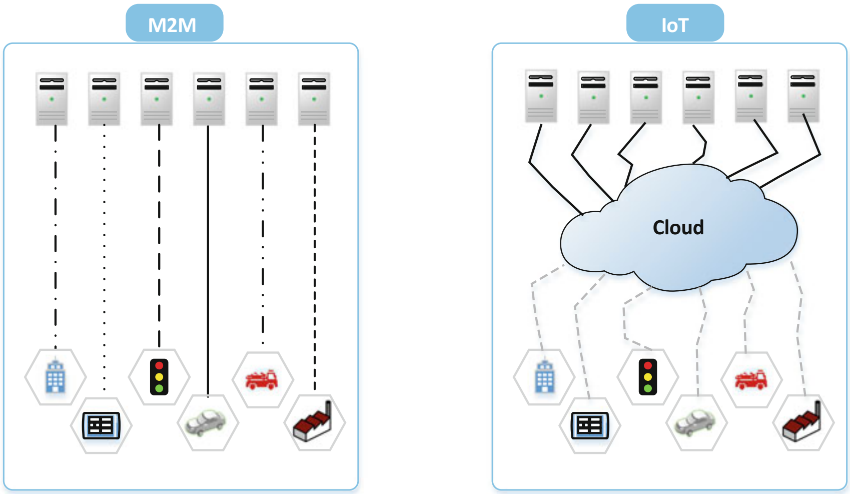


Fig. 2.12 Machine-to-Machine (M2M) and Internet of Things (IoT) connectivity for AVs

2.4.2 Internet of Things Platform for Autonomous Driving

A typical IoT platform is an integrated system which is capable of supporting millions of simultaneous device connections to generate a large volume of data to be transferred and processed in cloud computing. There are four main components in a typical IoT platform as depicted in Fig. 2.13. Four components are involved with IoT-AV platform: (1) first component is sensors and hardware devices which are the fundamental components and collect various data types from physical world, (2) the second component is the communication network which is normally based on wireless technologies such as Wi-Fi or cellular technologies (3G, 4G, 5G), (3) the third component is big data which represents the volume, velocity, and variety of data being generated; this data needs to be transferred, stored, and proceed, (4) the forth component of the platform is cloud where the data will be stored and processed as cloud provides several processing, analytics and storage services. IoT applications are traditionally hosted in the cloud and can provide feedbacks and decisions to the physical systems. In the case of AVs, cloud will be the centralized management system where all the software components and monitoring tools will be implemented.

IoT for autonomous driving is transforming the transportation system into a global heterogeneous vehicular network. IoT provides several benefits including dynamic information services, smart vehicle control, and applications to reduce

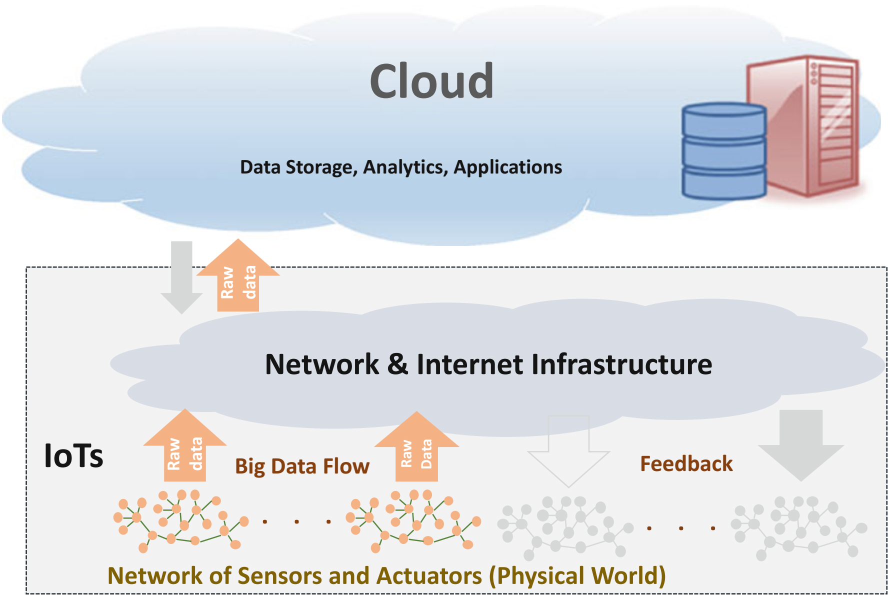


Fig. 2.13 Typical components of an IoT platform

insurance rates and reduce traffic congestions and possibly accidents. In order to create an IoT platform for vehicle, we need to extend the platform in Fig. 2.13 to make up a new ecosystem including the main elements and their interactions and then introduce a network model consisting of the intra-vehicular model and the environmental model. As mentioned before, there are a large number of sensors and hardware devices in the typical IoT platform. In this platform, there are two separate data acquisition components of an AV which are including (1) using data from own sensors, exchanges data with others in neighbourhood, and (2) IoT platform as collection place for large amounts of data from different gateway (parking, traffic information, transport, environmental information) by connected devices (parking spot, train, entertainment, traffic lights, bicycle, pedestrians, working areas, weather conditions, other vehicles). This is where the power of heterogeneous data sources and big data analytics come to picture to provide more comprehensive intelligence for AVs.

2.4.3 Internet of Things Ecosystem for Autonomous Driving

An IoT-based vehicle ecosystem is comprised of six components that interact with each other including: (1) vehicle, (2) person, (3) personal device, (4) network infrastructure, (5) sensing device, and (6) roadside device. Vehicles can be all nearby vehicles which can create a communication link to exchange relevant information such as traffic and road conditions, alerts, and other physical parameters in the ecosystem. Person includes people that request or access a service in the IoT ecosystem. Personal device is a device that belongs to any person in the ecosystem person (e.g. driver, passenger, cyclist) and uses or provides a service. Network infrastructure refers to all devices in the communication network that are used to transfer data in the ecosystem. Sensing device can be sensors and actuators that collect data about the vehicle’s parameters, person’s health levels, and environmental variables. For instance, this information can include tire pressure, fuel consumption, vehicle temperature for the cars and blood pressure, heart rate of the person and pollution, noise level, and weather conditions. Finally, roadside device is the transportation environment such as traffic lights, information screens or radars that have the ability to disseminate relevant information about traffic and road conditions, accidents, or possible detours.

The essential part of this IoT-based ecosystem is that the interaction among all IoT elements will cause a multi-level data exchange. This interaction, known as Device-to-Device (D2D) interaction may involve many devices (inside and outside of the vehicle) which can communicate, collect, store, and process information or make decisions with no or less human interventions. As proposed in[36], six types of D2D interactions have been identified as illustrated in Fig. 2.14. These interactions are Vehicle-to-Vehicle (V2V), Vehicle and Personal (V&P) device, Vehicle and Roadside (V&R), Vehicle and Sensor (V&S), Vehicle and Infrastructure (V&I),

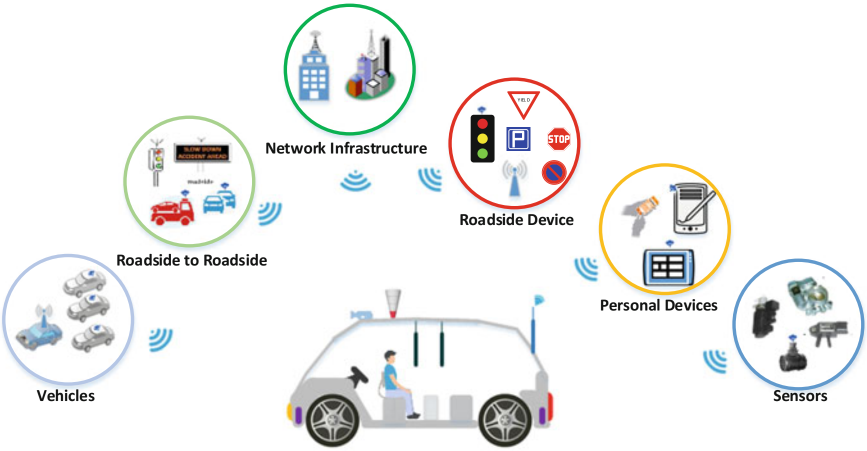


Fig. 2.14 Interaction model for IoT-based ecosystem for an autonomous vehicle

and Roadside and Personal (R&P) device. Additionally, there are two internal interactions namely, Roadside-to-Roadside (R2R) and Sensor & Actuator (S&A).

As can be seen in Fig. 2.14, sensors and some of the personal devices are within the AV and considered as internal interactions and the rest are more external interactions and can be considered as environmental information.

2.4.4 Edge Computing for Autonomous Vehicles

Current IoT platforms for AVs do not enable low-latency and real-time data processing and require offloading data processing to the cloud as shown in Fig. 2.13. The cloud allows access to storage and computing resources from anywhere and facilitates development and maintenance of applications, and related data. Although cloud computing optimizes resource utilization, it cannot provide an effective solution for hosting smart applications required in AVs. These bring several issues and challenges which hinder adopting IoT-driven services for AVs, namely:

- Transferring a large amount of data over the cloud network may incur significant overhead in terms of time, throughput, energy consumption, and cost.
- The cloud may be physically located in a different geographical region, so it is not possible to provide required services for AVs with reasonable latency and throughput.
- Real-time processing of large quantities of IoT data will increase the workload for providers and cloud data centre, with no benefit for the applications and users.
- Existing heterogeneity in hardware and software components of IoT sensors and devices.

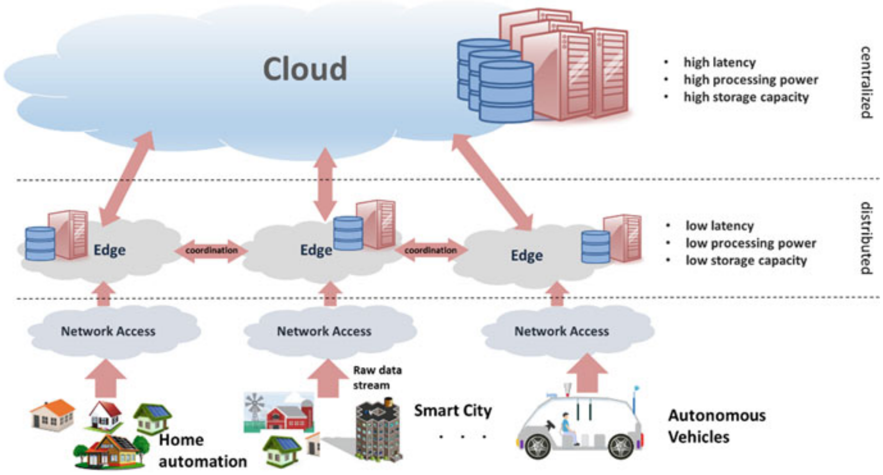


Fig. 2.15 Edge computing for IoT-based autonomous vehicles ecosystem

- Do not always integrate well together.

To address these challenges data analytics could be performed at the network edge near where the data is generated to reduce the amount of data and communications overhead [37]. This concept is called *Edge computing* (or Fog computing) as illustrated in Fig. 2.15. This emerging technology promises to deliver highly responsive computing services, scalability and privacy enforcement, and the ability to mask transient cloud outages [38].

As can be seen in Fig. 2.15, AVs will be connected to the edge devices using wireless communication network to access to real-time data analytics for required applications. Edge devices can collaborate with other edges in the vicinity, thereby creating a local peer-to-peer network beneath the cloud.

Data analytics at the edge of the physical world, where the IoT and data reside introduces an intermediate layer between the data source and the cloud as depicted in Fig. 2.16. By comparing the architecture of cloud computing in Fig. 2.12 and edge computing in Fig. 2.16, the edge computing provides on premise data analytics as well as the capabilities for IoT devices to communicate and coordinate with each other in a distributed environment and with the cloud [39].

Edge computing can be considered as an extension of older technologies such as peer-to-peer networking, distributed data, self-healing network technology, and remote cloud services.

It provides several advantages over standard centralized cloud architectures such as optimizing resource usage in a cloud computing system and reducing network traffic, which reduces the risk of a data bottleneck. Edge computing also improves security and privacy by encrypting data closer to the network core and keeps the private data away from shared cloud environments.

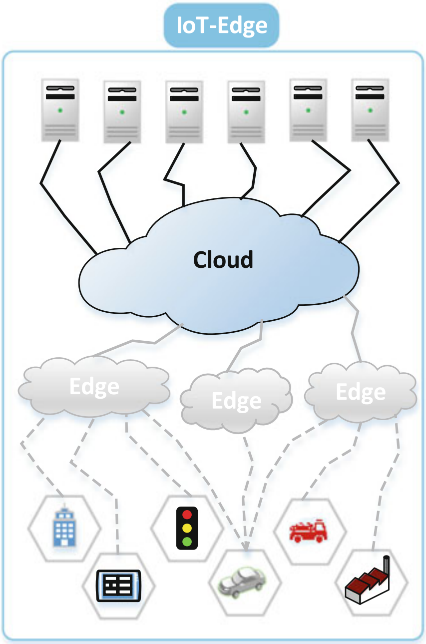


Fig. 2.16 Edge computing for IoT connectivity in AVs

In order to have a better view, Table 2.6 compares edge with cloud computing. As the data are pre-processed, filtered, and cleaned in the edge prior to offloading to the cloud, the amount of transmitted data is much less than the data collected by IoT devices. Also, the analytics on the edge is real-time while the analytics on the cloud is offline. Edge generally has limited computing power and storage compared with the cloud, however, processing on the cloud incurs higher computation latency. The edge offers a high level of fault-tolerance as the tasks can be migrated to the other edge in the vicinity in the event of a failure which is an important factor for AVs as the reliability is one of the main requirements.

Edge device may employ various types of hardware such as computing boards (e.g. Raspberry Pis), multi-core processor, FPGA, or GPU with fine granularity versus a cluster of homogenous nodes in the cloud [40]. Each edge device employs fixed hardware resources that can be configured by the user for each application, whereas the allocated resources are mainly intangible and out of user's control in the cloud. An advantage of edge is the ability of integration to mobile IoT nodes which is essential for AVs. In this case, multiple edge devices in close proximity dynamically build a sub-system in which edge devices can communicate and exchange data. Cloud offers a proven economic model of pay-as-you-go while edge is a property of the user. Edge devices could be battery-powered, so they need to be energy-efficient while the cloud is supplied with a constant source of power with possible energy-efficient resource management.

Table 2.6 Edge vs. Cloud computing

Characteristic	Edge	Cloud
Processing hierarchy	Local data analytics	Global data analytics
Processing fashion	In-stream processing	Batch processing
Computing power	GFLOPS	TFLOPS
Network Latency	Milliseconds	Seconds
Data storage	Gigabytes	Infinite
Data lifetime	Hours/days	Infinite
Fault-tolerance	High	High
Processing resources and granularity	Heterogeneous (e.g. CPU, FPGA, GPU) and fine-grained	Homogeneous (Data centre) and coarse-grained
Versatility	Only exists on demand	Intangible servers
Provisioning	Limited by the number of edge in the vicinity	Infinite, with latency
Mobility of nodes	Maybe mobile (e.g. in the vehicle)	None
Cost Model	Pay once	Pay-as-you-go
Power model	Battery-powered/Electricity	Electricity

2.4.5 Integrating Artificial Intelligence with Edge Computing for Autonomous Vehicles

In order to have AI model for AVs using edge computing, we need to modify the traditional cloud-based model where all data storage and analytics are happening in cloud. This traditional model is presented in Fig. 2.11 where the control mechanisms and database system will be implemented in cloud. In order to improve this model, we need to divide the process and planning section (Fig. 2.11b) into two modules to be handled by edge and cloud collaboratively. Figure 2.17 shows AI-based AV using edge computing where collected data from AV will be transferred to the edge node for pre-processing and decision-making. The data from IoT sensors will be analysed locally in the edge while data of the edge nodes is collected and transmitted to the cloud for offline global processing and less time sensitive decision-making. So, time-sensitive decisions such as obstacle detection or crash avoidance will be performed in the edge node in much shorter time. Whereas, the data about road, traffic and driving pattern are analysed in the cloud to improve the road safety and better driving experience. The AI models implemented in the edge node can be dynamic and updated based on the policies, and relevant rules and regulations and customer requirements. As the data are pre-processed, filtered, and cleaned in the edge node prior to offloading to the cloud, the amount of transmitted data is lower than the data generated by IoT sensors in AVs. This can save considerable amount of bandwidth and cost.

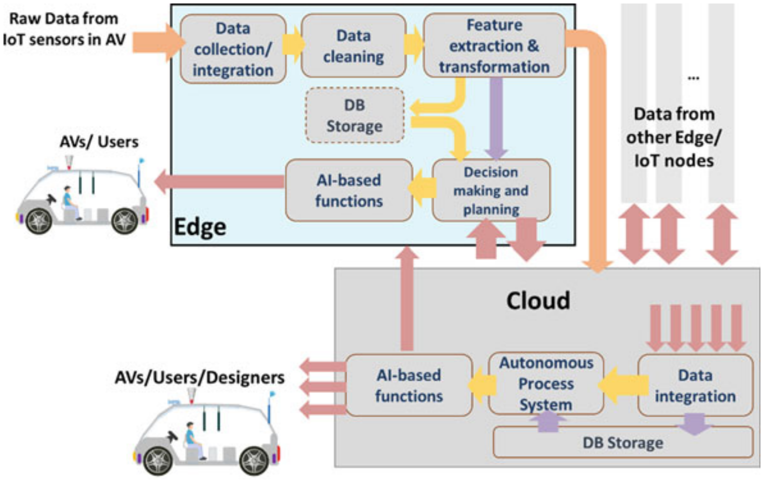


Fig. 2.17 AI-based autonomous vehicles using edge computing

2.5 Conclusions

The growth of Autonomous Vehicle (AV) in recent years creates a new trend to adopt various smart techniques and technologies to improve the performance and quality of automatic decision-making. The integration of Artificial Intelligence (AI) and Internet of Things (IoT) for AV provides high-performance embedded systems that can be utilized in environment to enable more dynamic and robust control systems. While the main software components of AVs are traditionally host by cloud computing systems, new edge computing paradigm has emerged to address some technical challenges such as latency, network bandwidth, and security. The concept architecture of a new AI-based AV using edge computing is proposed in this chapter and can be considered as a fundamental architecture for future research.

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