The Internet of Things for Smart Roads: A Road Map From Present to Future Road Infrastructure

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Abstract—Smart roads can potentially improve the safety and efficiency of present transportation systems and promote the future mass deployment of connected and autonomous vehicles (CAVs). In this article, based on the experience and lessons we learned from our research, field implementation, and industry engagement, we present our view about the phased and spiral development of smart roads and CAVs. A particular focus is on the development of an Internet of Things (IoT)-based system for smart roads to enable construction of a digital twin of the traffic and road system and various applications that can be built on that basis to improve the traffic safety and efficiency of current transportation systems, and the evolution of the IoT system to support the future mass deployment of CAVs.

Smart roads or *smart highways* refer to the application of new generations of sensing, computing, and communication technologies, such as vehicular networks, the Internet of Things (IoT), cloud computing, big data analysis, and artificial intelligence for the accurate and real-time sensing and communication of traffic and road conditions so as to accurately capture the current status of roads, each vehicle on the road, and predict their future development trend [1]. The sensed data are exchanged among vehicles, roadside units, road-embedded beacons, and road management authorities via a suite of communication technologies, including vehicle to everything (V2X), 2/4/5G, Wi-Fi, low-power wide area network (LPWAN), and optical fiber to achieve digitization of road assets, vehicle–road collaboration, and intelligent traffic and road management, which ultimately serve to improve traffic safety and efficiency, reduce construction and maintenance costs, and pave the way for the future mass deployment of connected and autonomous vehicles (CAVs) [2]–[4].

Smart roads provide a cost-effective alternative to building new roads for improving traffic safety and efficiency. Through a more comprehensive information coverage of roads, vehicles and human drivers can be informed of hazardous traffic and road conditions, adverse weather conditions, traffic congestion, and so on, thereby enabling a suite of safety- and efficiency-related applications. Furthermore, the fine-grained and real-time road and traffic information enables road authorities to exert finer traffic control, such as lane-level traffic control, ramp metering, and so forth to improve traffic safety and efficiency. According to the 2014 Victorian Auditor-General's Report "Using ICT to Improve Traffic Management," by implementing incident-response capability, lane-use management, variable-speed-limit signs, dynamic message signs, and closed-circuit TV (CCTV) along the 75-km freeway corridor from Werribee to Narre Warren, the travel time was reduced by 48%, accidents were decreased by 30–60%, and greenhouse gas emissions were reduced by 11%.

Smart roads are also important for the future mass deployment of CAVs. Presently, CAV technologies have advanced to the stage where autonomous driving becomes feasible in benign weather conditions and simple environments, such as highways, low speed and confined environments, mines, and docks. However, autonomous driving remains challenging in complex terrains and urban environments, including road intersections, tunnels, underground, and poor weather conditions. According to Waymo CEO John Krafcik, fully autonomous cars capable of driving in all weather and road conditions may require decades to achieve [5]. This statement has been corroborated by numerous recent fatal CAV accidents where all the major players, including Uber, Telsa, and Waymo, were involved. Through vehicle–road collaboration, smart roads help to augment the safety and reliability of CAVs by providing more accurate and beyond-line-of-sight road information difficult to acquire by CAV onboard sensors, thereby promoting their mass deployment. After smart roads have become ubiquitous, they may further contribute to lowering the sensing requirements of CAV onboard sensors, which helps to reduce the costs of CAVs, making them more economically affordable.

The implementation of CAVs, smart roads, and vehicle–road collaboration, however, has been largely limited to the experimental stage. A predicament hindering the large-scale deployment of smart roads and CAVs is attributable to the so-called "chicken-or-the-egg" causality dilemma: on the one hand, the mass deployment of CAVs relies on the sensing and communication support of smart road infrastructure to guarantee their safety and reliability; on the other hand, the large-scale implementation of smart road infrastructure, particularly smart roads for CAVs, depends on the mass deployment of CAVs because without a sufficiently high penetration of CAVs, there is no business case supporting the large-scale implementation of smart road infrastructure. Therefore, despite the technical prominence of smart road (and vehicle–road collaboration) technologies and their exciting potential to improve CAV safety and efficiency, their implementation is struggling as these technologies were invented to solve problems for future CAVs, which do not exist in current transportation systems dominated by human-driven vehicles. Doubts naturally arise as to why we should invest heavily to build smart roads now when the problems they intend to solve have yet to appear [6]. To this end, we present our humble and plausible views about the phased and spiral development of smart roads and CAVs and how they can support each other during each development stage. We further present an IoT-based system for smart roads, their technical advantages and use cases, and how the IoT for smart roads can serve to improve the traffic safety and efficiency of the current transportation system and evolve to support future CAVs.

Phased and Spiral Development of CAVs and Smart Roads

In this section, we argue that the transition to CAVs and smart roads may not be complete in one step. Instead, the transition to CAVs and smart roads may follow a phased and spiral development process and take a rather long time period, possibly spanning decades.

First, *CAVs* do not refer to a single technology and should not be viewed as a whole. Instead, CAVs comprise a suite of technologies and functionalities at different development stages [7]. Some are ready for market now while others are still in their infancy. According to a recent report in 2020 by the MIT Task Force on the "Work of the Future," fully autonomous vehicles will take at least a decade to deploy over large areas [8]. Some other experts pointed to an even longer time horizon. However, this does not mean that we need to wait that long to enjoy the benefits of CAVs. Along the way toward developing fully autonomous vehicles, some of the more mature functionalities such as blind-spot detection, adaptive cruise control, lane-keeping assistance, parking assistance, collision-avoidance systems, and so on have already found their way into some newly released vehicles [9]. Some other more sophisticated functionalities such as driving in complex terrains and poor weather conditions will take longer to mature. Therefore, the development of CAVs itself takes phased development stages. This has been manifested by the fact that CAVs are classified into five autonomous driving levels [10].

Second, the development of road technologies has always been driven by the progress of vehicles and will therefore follow a similar phased development process. If we look back at the development history of road technologies, we never build roads waiting for new types of vehicles to come, and the development of roads has always been a lag follower of vehicles. When cars first appeared, they drove on roads designed for horse carriages. When the number of cars became large, we started to build concrete roads more suitable for vehicle driving. When their number further increases and the speed became higher, along came traffic signals, signalized intersections, sophisticated traffic control systems, and highways. Therefore, historically, the development of roads has always been a lag follower of vehicle development because, in this case, vehicles represent demand while roads are developed to meet the demand. As an analogy, smart roads for CAVs are unlikely to become commonplace until there is a sufficiently high penetration of CAVs because without a sufficient number of CAVs, there is simply no demand nor business case for smart roads dedicated to CAVs.

Finally, the chicken-or-the-egg causality dilemma mentioned previously also means that the transition to CAVs and smart roads will follow a phased and spiral development process, as shown in Figure 1. As there are very few CAVs on roads now, the focus of smart roads now should be on improving the traffic safety and efficiency of current transportation systems dominated by human-driven vehicles (L0–L2 vehicles, adopting the terminology of five levels of autonomous vehicles) and reducing their costs. Only in this way, can smart roads gain widespread acceptance and support by transportation stakeholders. As smart roads become more ubiquitous, the more comprehensive information coverage provided will facilitate the deployment of next-stage CAVs, say, L3 vehicles. Only when the penetration of L3 vehicles has become sufficiently high, will smart roads for L3 vehicles become economically justifiable, be possibly considered for large-scale deployment, and so on, until the full potential of both smart roads and CAVs are unleashed.

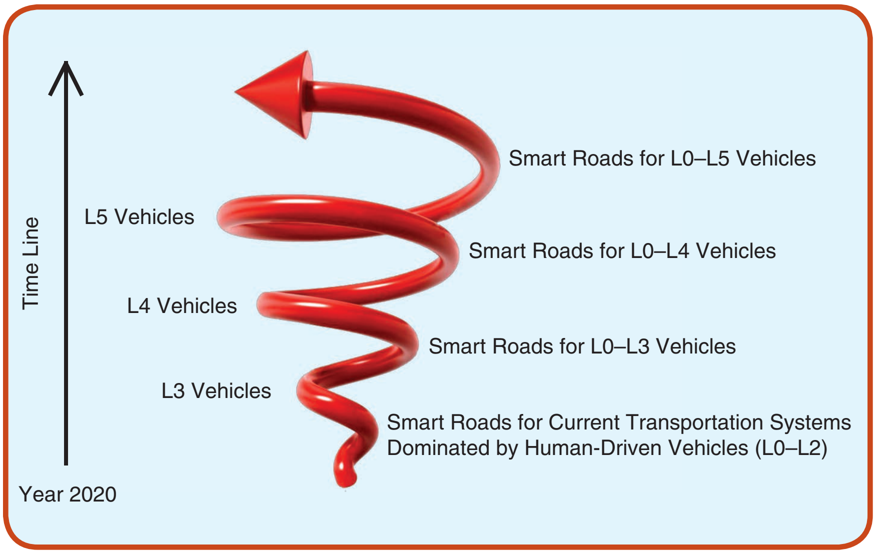


FIG 1 An illustration of the phased and spiral development of CAVs and smart roads.

The IoT for Smart Roads

In this section, we present an IoT-based approach for smart roads, which may potentially fulfill the aforementioned vision of achieving a phased and spiral development of CAVs and smart roads in a cost-effective way. Specifically, we first report the design of small but powerful, ubiquitously deployed, solar-powered, road-embedded plug-and-play types of IoT devices, which can be integrated with multiple sensors, such as temperature, humidity, light, vibration and magnetic sensors, LED lights, and so forth. Then, we illustrate the use of these IoT devices in a tightly integrated, node-edge-cloud architecture to realize a digital twin of the road traffic system to capture the microscopic behavior of each vehicle with lane-level accuracy. Furthermore, we demonstrate the coupling of ubiquitously deployed IoT devices with other sparsely deployed sensing devices such as CCTV, millimeter-wave (mm-wave), or laser radar at strategic locations to create an even more powerful digital twin with rich traffic information through multisource data-fusion techniques. Finally, use cases of the IoT system are illustrated to demonstrate traffic safety and efficiency applications. Figure 2 presents the proposed IoT system, which comprises IoT devices, BSs, and the cloud.

IoT Devices

IoT devices are regularly spaced and extensively deployed along lane-division lines, road-boundary lines, or near road surfaces, as shown in Figure 2. Each IoT device is equipped with a battery, solar panel, plethora of small and low-power sensors (as mentioned previously), LED lights, communication module, and low-power microcontroller (MCU). These IoT devices can function normally in a temperature range of –40–80 °C and constitute the node devices in the node-edge-cloud architecture. For tunnels or other underground environments where solar power is not available, a variant can be readily designed using an external power supply. Each IoT device is responsible for sensing nearby traffic and road conditions and communicates with nearby IoT devices using low-power Bluetooth communication, and with its base station (BS) using LPWAN technology such as long range (LoRa), narrowband Internet of Things, or LTE Category 1. The two former technologies offer very low power consumption but higher latency and modest data rates, while the latter technology provides medium communication speed and lower latency at the expense of higher power consumption. Mainly limited by power consumption, the popular long-term evolution-vehicle (LTE-V), cellular V2X (C-V2X), and dedicated short-range communication (DSRC) technologies are currently infeasible to be embedded into these IoT devices. Each IoT device will process its measurements locally and transmit information of interest only to its associated BS or nearby IoT devices.

Specifically, for the highway applications detailed later in this article, an RM3100 geomagnetic sensor with a maximum sampling frequency of 600 Hz is integrated into the IoT device. It comprises two Sen-XY-f sensors, a Sen-Z-f sensor, and MagI2C control chip [11]. With the geomagnetic sensor, the measurement of magnetic field intensity in 3D space can be obtained. When a vehicle enters the detection range of an IoT device, it causes a local disturbance of the magnetic field, which is detected by the IoT device. Therefore, by collecting and analyzing the detected changes of the local magnetic field, accurate vehicle detection can be achieved. In the actual deployment, the sampling frequency of the RM3100 is set to 200 Hz to reduce the amount of calculation and power consumption. The geomagnetic sensor can be further integrated with a vibration sensor

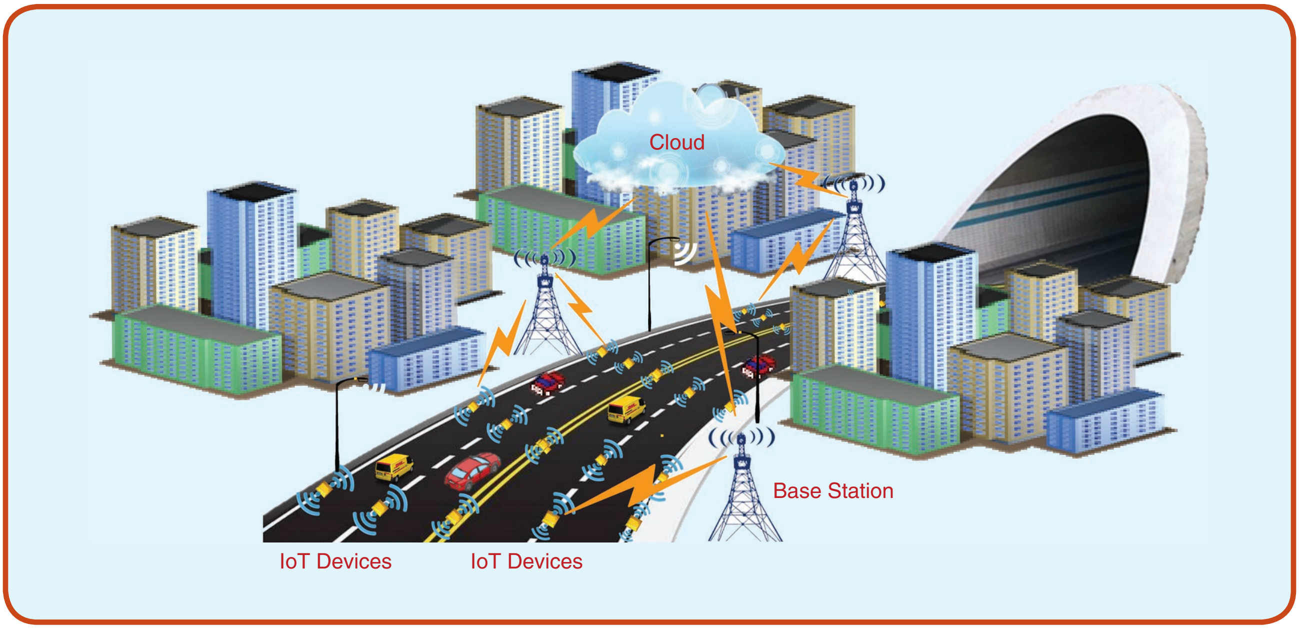


FIG 2 An illustration of the proposed IoT system.

to achieve more accurate vehicle detection. These local data are processed by an MCU, which in this case is a 32-b advanced reduced-instruction-set computing machine whose core is the STM32F103RCT6 MCU of the cortex-M3. The MCU processes the large amount of raw data collected by these sensors, translates them into a vehicle-passing event parameterized by the vehicle's arrival and departure times, vehicle type, and so on and then transmits the much lower amount of data to its associated BS via LoRa.

Apart from sensing, processing, and communication, LEDs in the IoT device can be used to disseminate various traffic events. The LEDs can support various colors, such as red, green, yellow, and white. Some safety applications such as distance keeping are performed entirely at the node level by IoT devices. For example, when a vehicle passes, the IoT device changes the LEDs into red or yellow for a predetermined amount of time to alert the following drivers to keep a safe distance. As explained later, LEDs can also be controlled by the cloud to respond to traffic events. For instance, when a traffic collision is detected, the cloud can change the LEDs in IoT devices within a certain distance from the traffic collision to red so as to alert nearby drivers, thereby avoiding additional accidents. Or in poor weather conditions, the LED's color and brightness can be changed by the cloud to mark lane boundaries or alert drivers of traffic hazards, thereby promoting road safety. Of course, the combination of LED color and flicker frequency can also be used to communicate traffic events to CAVs via detection by CAV's onboard cameras. Depending on the applications, other types of sensors may be embedded into IoT devices. For instance, for pedestrian detection, we used a combination of four types of sensors: microwave, infrared, magnetic, and temperature to achieve reliable detection in all weather conditions.

BSs

BSs, which may be powered by a solar power panel or an external power supply, constitute edge devices in the node-edge-cloud architecture [12]–[14]. These BSs collect information from IoT devices in their domains using LPWAN technology, specifically the LoRa communication module SX1278LoRa, conduct data association and vehicle tracking, which allows for association of the data reported by different IoT devices with individual vehicles generating the data, and estimate vehicle trajectory, speed and position, lane change, and so forth. They also conduct other local information processing, such as fusing data from IoT devices and cameras, mm-wave/laser radars, and local decision making. Then, the BS communicates to and receives relevant information from cloud servers using wired or wireless communication such as optical fiber or 2/4/5G and disseminates information to IoT devices or vehicles in its domain.

The Cloud

The cloud, which may be made of locally managed cloud servers or from external cloud service providers, is responsible for assembling information from all BSs, conducts central information processing and decision making, forms a digital representation of the physical system in the form of a digital twin, and converts various information from BSs or the IoTs (indirectly via BSs) into a form of interest to stakeholders, such as traffic events like congestion, retrograde, accidents and abnormal vehicle stopping, vehicle trajectories, road health status, traffic status, and so on. The cloud also controls IoT devices and road-information boards, if available, to respond to traffic events. A tightly integrated node-edge-cloud architecture, where data processing and communication happen at each layer and are jointly optimized across layers, not only facilitates local processing and decision marking but also greatly reduces data communication load, crucial for meeting the stringent low-power consumption requirements of node and edge devices, and reduces communication latency, vital for meeting the real-time requirements of traffic and safety applications. Figure 3 depicts photos of the actual IoT device and BS and their road deployment.

Compared with other popular technologies used for traffic and road sensing such as CCTV cameras and mm-wave/laser radars, an IoT system has the following several advantages:

- An IoT system can achieve much higher accuracy than other sensing devices and individual IoT device through data fusion from ubiquitously deployed IoT devices. Each IoT device is low cost and small in size, capable of low-medium accuracy measurements only. However, through data fusion from a large number of IoT devices, the system can achieve an accuracy that is higher than some of the high-end sensing devices. For example, each IoT device measures the number of passing vehicles with its magnetic sensor and is able to achieve an accuracy of 95% [15]. If a vehicle passes 10 devices, the probability that the vehicle will not be detected by any of the 10 devices equals $(1-0.95)^{10}$. As a result, by fusing the measurements of a larger number of devices, theoretically, an accuracy rate arbitrarily close to 100% is achievable. Consider the second example of road health monitoring. The abnormal vibration caused by passing vehicles is often a precursor of road health problems and can be used for crack and pothole detections [16]. A single measurement is often meaningless; however there may be hundreds or thousands of vehicles passing by a device daily. Together with the dense, spatial deployment of IoT devices, the extensive spatiotemporal big data form a powerful basis for a road health diagnosis.

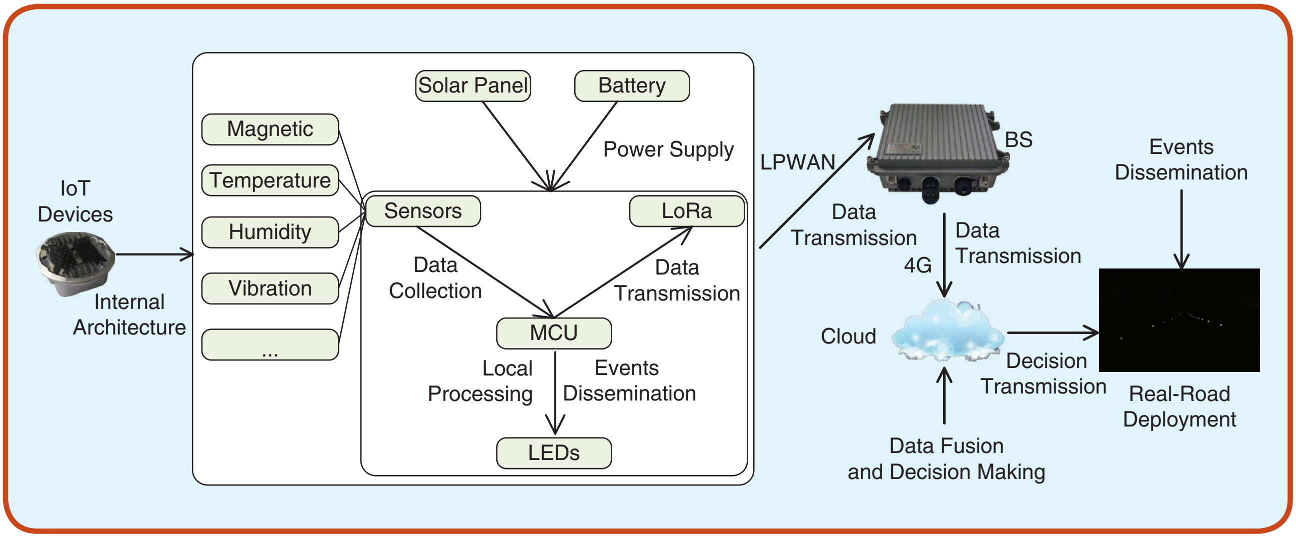


FIG 3 Photos of the IoT device and BS. The left portion of the figure shows the IoT device. The top-middle features the BS (without antenna), and the right portion shows the real-road deployment photo taken at night. (Source: Shenzhen Daison Intelligence Pty Ltd; used with permission.)

- The large number of deployed IoT devices bring measurement devices closer to events of interest; this greatly alleviates difficulties in acquiring accurate measurements, which often grow exponentially with distance.
- An IoT system has a minimal reliance on the power and communication infrastructure or installation platform, which makes the rapid and cost-effective deployment of smart road infrastructure feasible.
- The large number of deployed IoT devices also means the failure of a small number/percentage of IoT devices often has little impact on the system's performance. Therefore, the resulting system is much more robust than those relying on a small number of high-end and more expensive/powerful sensing devices.
- An IoT system has much lower costs. As IoT devices are deployed along lane-division or road-boundary lines and an IoT device is capable of achieving a detection range of 5–7 m, i.e., lane-level detection, the costs will increase with the number of lanes. For a one-way road with two lanes, IoT devices are deployed along the two boundary lines, as displayed in Figure 4. For a one-way road with three lanes, a deployment in the middle of the road along the lane-division lines is necessary. Consequently, for a two-way road with four lanes, the costs are roughly RMB400,000/km or US$61,000/km; for a two-way road with six lanes, the costs are roughly RMB800,000/km or US$122,000/km. To achieve the same coverage, the equipment costs using cameras or mm-wave/laser radars are at least three-times higher. Considering the requirements for power and communication supply and higher installation costs, their costs are even higher. Furthermore, extensively deployed LEDs in IoT devices allows for traffic control at a much-finer granularity, which opens the door to a plethora of traffic and safety applications.

FIG 4 An illustration of a digital twin of the road traffic system. The IoT devices are deployed along both sides of a two-lane freeway at Qinglian Freeway near Shenzhen, China.

Due to the salient advantages of an IoT system, its deployment has gained momentum rapidly. We have deployed IoT systems in six highways spread across China, including the Shandong, Shannxi, Guangdong, Guangxi, and Hunan provinces. The number of new deployments will at least double in 2022.

Data Fusion at the Edge and Cloud Levels

In this section, we illustrate the use of data fusion at the edge and cloud levels to construct a more sophisticated digital twin from relatively simple measurements of IoT devices. An important lesson we learned from wireless sensor networks is that through the cooperation of a large number of networked sensors, each sensor capable of simple and low-medium accuracy measurements only, a sensor network system can be constructed with much more powerful functionalities and better accuracy than a system formed out of a small number of expensive and powerful sensing devices. What we present next is essentially an application of this principle. Specifically, using the aforementioned IoT devices, combined with digital maps and/or road building information models, two digital twin systems can be constructed for road traffic system and road health and asset-monitoring system, respectively. These two systems can sometimes be merged into a larger system. As they often serve different stakeholders and have quite different functionalities, in this article, we separate the two systems. Due to space limitations, the focus of this article is on introducing the first system. The second system can be formed using temperature, humidity, light, and vibration measurements of IoT devices, assisted by lane level vehicle type and vehicle-count measurements.

As IoT devices are deployed along lane-division or road-boundary lines, each IoT device is able to measure the number of passing vehicles and the time instants when these vehicles pass at a lane level using its magnetic sensor [15]. Each IoT device reports to its associated BS the discrete-time instant when a passing vehicle is detected.

We now explain how to use the discrete-time measurement reported by IoT devices to form vehicle-trajectory estimation. At the first IoT device along the travel direction, a Kalman filter can be initialized using each reported measurement. The parameters of the Kalman filter can be empirically estimated. Each Kalman filter represents an estimate of the trajectory of a vehicle. The number of Kalman filters initialized is equal to the number of measurements [17]. At the second IoT device, a validation window can be formed around the estimated time of arrival—obtainable from the Kalman filter—and the empirically estimated minimum and maximum speeds of a vehicle, which are used to set the width of the window. Any measurements from the second IoT device falling into the validation window are considered possibly associated with the vehicle corresponding to the validation window. If there is more than one measurement in a window, a joint probability density association (JPDA) or multiple hypothesis testing procedure can be invoked to resolve the ambiguity; if there is no measurement falling into the validation window, we may skip to the third IoT device and repeat the same procedure used for the second IoT device. If there are a predetermined number of consecutive IoT devices having no measurement in the window, the trajectory is deemed a false trajectory and removed; if there are measurements falling into none of the validation windows, a new trajectory may be initialized.

Starting from the third IoT device, the aforementioned estimated minimum and maximum speeds of a vehicle can be replaced by the estimated process noise covariance of the Kalman filter to set the width of the validation window. As the number of IoT devices increases, the Kalman filters start to converge and the associated validation window sizes become smaller. At that time, it can be quite unusual to have more than one measurement falling into the same validation window. The aforementioned procedure is known as *joint data association and tracking* [18]. Note that trajectory initialization is required only at the first BS along the travel direction. The subsequent BSs will inherit the trajectories estimated at the first BS, except for BSs at ramp locations where new vehicles may join or existing vehicles may depart.

The vehicle-trajectory initialization and estimation will first be done at lane level. Then, for a road with multiple lanes, lane-level estimation will be combined to form more sophisticated multilane road estimations. For example, lane-change estimation can be formed jointly from lane-level estimation by a vehicle disappearing from a lane (death process) and then emerging in another lane (birth process).

At the cloud level, trajectory estimation at individual BS levels (or edge levels) can be stitched together to form a complete view of each vehicle on the road, their instantaneous position, speeds and trajectories, thereby forming a digital twin of the road traffic system. Figure 4 presents an illustration of the road traffic digital twin system at the cloud platform.

Data Fusion With Other Sensing Devices

In the previous section, we demonstrated the use of an IoT system to create a basic digital twin of a road traffic system. In many transportation applications, we need more information. For instance, for tracking the movement of hazardous vehicles, e.g., vehicles carrying hazardous materials or heavy trucks, we need to know information such as the vehicle's license plate number. Due to the types of sensors that can be fitted into small IoT devices, it may be difficult for an IoT device to acquire such information. However, an IoT system forms the foundation that readily allows other types of measurements to be fused into the system, upon which a digital twin with a much richer set of information can be built.

Specifically, the vehicle-trajectory information provided by an IoT system readily enables measurements from other types of sensing devices with disjointed and sometimes far-separated coverage areas to be associated. A naive application fusing the information from an IoT system as well as from other sensing devices can immediately enrich the information set provided. A more sophisticated fusion application will not only enrich the information set but also improve measurement accuracy beyond that which is achievable by individual systems. Consider, for example, the fusion of an IoT system with CCTV cameras. An IoT system can readily estimate the time when a vehicle passes a particular CCTV camera. A CCTV camera can acquire a vehicle's license plate, type, color, and more importantly, the timestamp of these measurements. Taking into account synchronization errors among different sensing devices, an algorithm can be readily designed using the time instant when a vehicle passes the camera as the basis for data association, which allows vehicle trajectories in an IoT system to be labeled with vehicle-identification information acquired from the camera. Furthermore, both the IoT system and camera are able to estimate traffic volume. A more sophisticated algorithm is able to fuse the common types of estimation from independent sources and achieves much-improved accuracy.

Use Cases

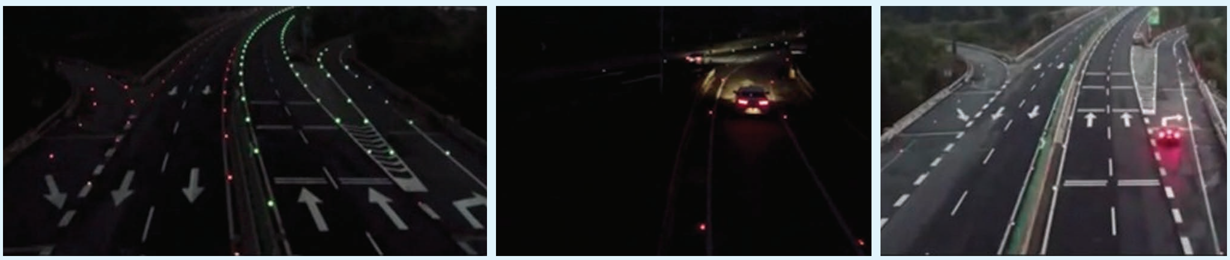
The digital twin illustrated previously allows for monitoring of the instantaneous status of each vehicle and provides a platform for lane-level traffic, traffic congestion, and traffic accident monitoring; lane-use management; and so on.

In addition to the aforementioned services, many standalone applications can be built using an IoT system. Particularly, we further emphasize that the LED light on an IoT device makes for easy interaction with drivers, especially at night or during poor-visibility conditions. By changing the color and frequency of light, information can be readily disseminated to drivers at a much-finer granularity than the popularly used message board. The integration of sensing, communication, computing, and message dissemination in an IoT system opens the door to a long list of possible applications, such as the following warnings: traffic accident, fog-area traffic, work site, intelligent lane-boundary marking, ramp merge, hazardous traffic, approaching vehicle on curved road, poor weather and road condition, wrong-way driving, and so on.

Figure 5 displays three of these applications: wrong-way driving, ramp merge, and fog-area traffic. For wrong-way driving warning, as shown in Figure 5, vehicles driving in the correct direction will see a green light while vehicles driving in the wrong direction will see a red light. For a ramp-merge warning, on detection of vehicles in the main road and estimation of a possible collision, the light in the ramp road will turn red or yellow to issue a warning to vehicles in the ramp road. Similarly, on detection of vehicles in the ramp road and estimation of a possible collision, a light in the merge area of the main road will turn red or yellow. Finally, for a fog-area traffic warning, when the visibility becomes low (measured by visibility sensors colocated with the BS), the traffic-warning function will be activated. When an IoT device detects a passing vehicle, it will switch its light to red or yellow and will remain that color for a predetermined time period, with LED brightness set according to visibility conditions. Therefore, visually, a vehicle is followed by a trail of red (or yellow) lights, which forms a lane-level forbidden zone behind the vehicle. In low-visibility conditions, a driver in the rear vehicle may not necessarily be able to see the front vehicle, but through the red/yellow light in the vicinity, the driver is alerted of a dangerously close distance to the front vehicle and prompted to keep a safe distance.

A Vision for Moving Toward Future Road Infrastructures

In this section, we discuss how an IoT system can evolve to support future CAVs. As explained in the "Phased and Spiral Development of CAVs and Smart Roads" section, we expect the transition to be phased, gradual, and driven by advances in CAV technologies and deployment. The interactions between smart roads and CAVs have to be reciprocal: when a particular smart road technology has been widely accepted and become mainstream, this may push car manufacturers to update their designs to better utilize the benefits of the technology; conversely, when a particular



(a) (b) (c)

FIG 5 An illustration of use cases of the IoT system. A (a) wrong-way driving warning, (b) ramp-merge warning, and (c) fog-area traffic warning. (Source: Shenzhen Daison Intelligence Pty Ltd; used with permission.)

CAV technology has been widely deployed, this may compel road authorities to adopt innovative road technology to better suit new types of CAVs.

Hopefully, the salient advantages of an IoT system and particularly its capability to serve the present transportation system may promote its widespread deployment before CAVs. In the early days when CAV deployment is scarce, the interactive evolution between an IoT system and CAVs may start by CAVs adapting their onboard algorithm with few hardware changes to better recognize 1) road/lane boundaries marked by IoT devices, 2) traffic hazards by learning the messages disseminated by IoT devices through the changing frequency and color of their LED lights, and so forth.

The comprehensive traffic and road information provided by an IoT system may also be conveyed to CAVs through telemetry, LTE-V, or other vehicle-to-infrastructure communication technologies. When the penetration of CAVs has grown to become a serious consideration, the BSs in an IoT system may be upgraded to support direct communication between BSs and CAVs. This can be done by plugging in a suitable communication module without replacing the entire BS. It may greatly reduce the latency and also makes local CAV control and decision making possible. Finally, when the penetration of CAVs further increases such that full-CAV support becomes economically justifiable, as depicted in Figure 6, IoT devices may be augmented with capabilities to communicate directly with CAVs, e.g., via visible-light communications (VLC) or other low-power, low-latency, and SRC techniques at that time. All other things being equal, our preference is VLC because of its easy integration into the LED lights already present in IoT devices.

The finer deployment granularity of IoT devices provides finer traffic information and control. We envisage that in the future, a fully developed IoT system will be able to provide all the traffic and road information required by CAVs, and in the meantime, guide the movement of CAVs. Our vision has been inspired by the fact that despite all the difficulties confronting CAVs, autonomous driving in railways has been a mature technology and widely applied. Road and road traffic environments are, however, known to be notoriously intricate. We hope that a ubiquitously deployed IoT system will bring "virtual rail" onto the road such that both road and road traffic environments become more regulated, thereby supporting the future mass deployment of CAVs.

In the following, we use localization as a more concrete example to illustrate how some future functionalities can be added into an IoT system to support CAVs. A key enabling technology for CAVs is lane-level vehicular-localization technology. The existing techniques can be broadly classified into two main categories: global navigation satellite systems (GNSS) and map and sensor based, such as the well-known simultaneous localization and mapping. GNSS-based techniques are unreliable or even unavailable in complex urban environments, tunnels, or underground. Map-and-sensor-based solutions suffer from difficulty in the real-time updating of high-precision maps (which are dynamically changing), occlusion of line-of-sight (LoS) path, and poor sensor performance in severe weather conditions. Therefore, accurate and reliable vehicular localization remains a great challenge in complex environments [19].

Using extensively deployed IoT devices as beacons, and distance and/or bearing measurements between vehicles and IoT devices, which can be acquired either through vehicle onboard sensors or through direct communications between the vehicle and IoT device, a cubature-information filter-based [20] tightly coupled architecture with fault detection and exclusion (FDE) for the integrated localization system can be developed, which works with the raw measurements from a GNSS, map-and-sensor-based IoT system directly. A tightly coupled architecture can make use of GNSS measurements even when fewer than four satellites are available and can also exclude faulty measurements (e.g., non-LoS or multipath IoT measurements, erroneous-vehicle onboard sensor measurements due to poor weather or occlusion, and erroneous pseudo-range measurements)

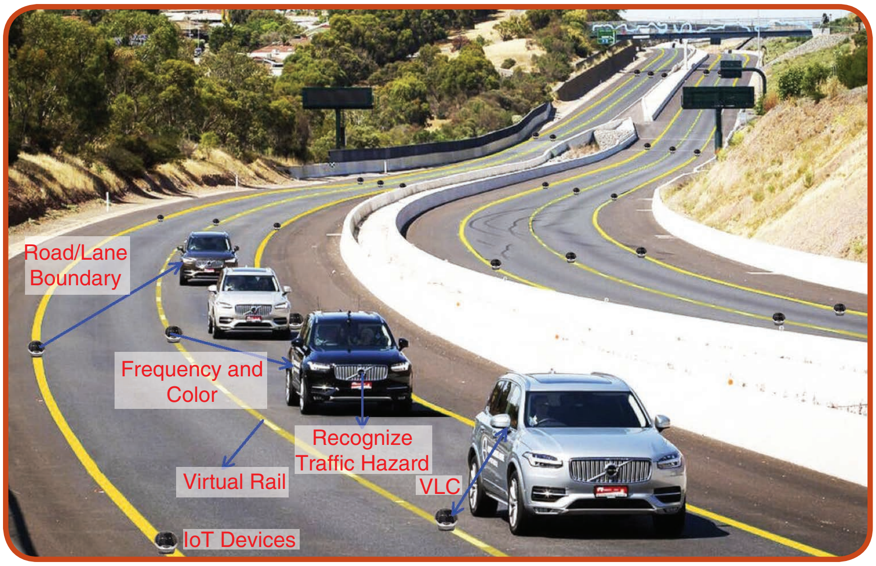


FIG 6 The IoT for future road infrastructures. VLC: visible-light communications. (Source: Shenzhen Daison Intelligence Pty Ltd; used with permission.)

using the measurements from other systems. Finally, weighted Kullback–Leibler divergence (WKLD) can be employed for FDE where a weight is added to each part of the Kullback–Leibler divergence to reflect the confidence that we have in them. The WKLD-based FDE will prevent erroneous measurements from all three systems from contaminating location estimates.

Conclusion

This article provides a forward-looking road map for the development of IoT systems for smart roads. The technical advantages and use cases of IoT systems were presented, and their evolution paths to support future CAVs were discussed. We hope that our discussion will spur interest and further investigations into the future evolution and interactions of smart roads and CAVs and the development of IoT systems.

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