Automotive Sensing for Smart Cities: Current Practices and Challenges

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Abstract: Recent technology advances, such as IoT, 5G, LPWAN and AI, have been making smart cities an increasingly appealing vision of future society. One indispensable basis in the research, development and implementation of smart cities is the urban sensing technologies that collect various data from urban area. Automotive sensing is a novel urban sensing technology where sensors are equipped to vehicles, like buses, taxi cabs or garbage trucks and utilize their mobility to help to conduct urban sensing tasks. In this survey, we summarize the emerging applications of automotive sensing in smart cities and also discuss the challenges that should be addressed to accelerate the development and application of automotive sensing in smart cities.

1. Introduction

The human society is continually challenged by various natural and man-made problems including but not limited to nature disaster, environment pollution, population aging, energy shortage and traffic congestion. Recent technology advances including IoT, 5G, LPWAN and AI have been making smart cities an increasingly appealing vision of future human society, where various kinds of data are collected and processed to generate useful information that motivates a number of novel applications to alleviate or solve the aforementioned problems, so as to improve the quality of life of inhabitants in cities [1, 2]. Such data range from environmental information, such as air quality and ultraviolet (UV) strength, through objects information, including traffic flow and road surface quality, to human information, such as density of habitants. One of the fundamental technologies in the research, development and implementation of smart cities is urban sensing technology, i.e. to collect the required data from urban areas. Pre-installed stationary sensors, mobile sensing with smart phones and the senses of participants' and software sensing of websites have being explored in various application scenarios [3–5].

During the last decade, extensive research effort has been devoted to the study of using vehicles in urban sensing, i.e., sensor(s) are installed in vehicles, like taxi caps, buses, cars and trucks, and collect targeted data as the host vehicles move around over a city. We term this sensing pattern as automotive sensing in this survey. Early research attempts on automobile sensing can be traced back at least to CarTel [6] and MobEyes [7]. The CarTel is a sensing system to collect, process and deliver data from on-board or external sensors on vehicles. Each vehicle relies on opportunistic wireless connectivity, including Wi-Fi and Bluetooth, or "data mules", i.e., USB flash memories, to deliver the collected data to a central for further analysis and visualization. A small-scale experimental system was implemented and run in Boston and Seattle for over a year, where the collected data was used to analyze commute times, analyze metropolitan Wi-Fi deployments, and for automotive diagnostics. In [7], the authors proposed a system called MobEyes to diffuse/harvest summaries of the sensed data, so as to reduce communication overhead and improve scalability. Based on experiment/analysis studies, it is reported that MobEyes is scalable up to thousands of nodes with reasonable overhead and diffuse/harvest latency.

In [8], the authors surveyed the automotive sensing platforms published by 2009. In particular, V2V (vehicle-to-vehicle communication)-based platforms and infrastructure-based platforms were carefully reviewed for a comprehensive understanding on the networking technologies used to collect, store and harvest the information generated in those automotive sensing platforms. Since the publication of [8], an increasing number of novel applications of automotive sensing have been reported in the literature for the research and development of smart cites.

In our opinion, automotive sensing draws so much attention from the research community of smart cities mainly for the following reasons. First, the recent development of vehicular electronics gives vehicles a powerful sensing capability. In order to improve the usability, performance or safety, various sensors have been integrated into vehicles, such as GPS, radar and driving recorder. Besides, the sensors in personal devices carried by the driver or passages like smart phones may also be used. These on-board sensors can be reused for various urban sensing scenarios and also significantly reduce the development and deployment complexity. It is also notable that the sensors can be powered by the battery of host vehicle, which is continuously being charged as far as its engine is working, leading to an almost inexhaustible

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power supply in most cases. Second, the advanced transportation system in modern cities makes automotive sensing a promising urban sensing technology for many application scenarios in smart cities in that the mobility of vehicles leads to a wide sensing area with a relatively less number of sensors, thus reducing the cost in deployment and maintenance. Third, the increasingly ubiquitous accessibility of wireless communication driven by the technology progresses in cellular network, WiFi and LAWAN has make it possible to gather the sensory data from moving host vehicles with an acceptable communication cost. While [8] serves as an excellent introduction to automotive sensing from the aspect of vehicular networking, the applications areas and related technologies have significantly evolved since the publication of [8]. Therefore, it is necessary to investigate the current progress and analyze the challenges, as as to deliver a general roadmap for those who want to apply automotive sensing to smart cities development. Driven by urgent social requirement and fast progress in related technologies, we envision that automotive sensing will become an increasingly popular urban sensing approach in the research and development of smart cities in the next decade.

The rest of the paper is organized as follows. In section 2, we review and classify the applications of automotive sensing for smart cities in the literature. Section 3 presents existing work and related discussion regarding the evaluation of sensing quality. Section 4 concludes this paper.

2. Applications of Automotive Sensing for Smart Cities

In this section, we review the automotive sensing applications/platforms reported in the literature for the research or development of smart cities. In particular, we classify these literatures into five categories, namely, transportation system, environmental monitoring, object detection, platform and others.

2.1 Transportation system

Transportation system is one of the initial application areas of automotive sensing. The applications in this category can be divided into two branches. The first branch is to detect the status of the host vehicle itself, like position, heading, and velocity. The second branch is to detect/estimate the status of transportation system via the data collected from host vehicles.

While space-based radio-navigation systems like GPS has become a standard vehicular equipment, their positioning accuracy does not meet the requirement in some key application scenarios, such as cooperative collision warning system [9], due to the mobility of vehicles or outage of satellite radio signals. In order to achieve a higher positioning accuracy, the work of [10–13] investigated joint data analytics using the GPS data and the mobility-related data obtained from in-vehicle sensors like wheel-speed/steering-angle sensors and gyroscope. In [10], the authors proposed a Kalman filter integrated estimation algorithm where GPS, wheel speed/steering angle and gyro serve as the input, and showed via experiment that a $< 1m$ estimation accuracy can be achieved even when GPS outage happened. Using similar kinds of sensor data, the work of [12] proposed an interacting multiple model filter of vehicular positioning for various

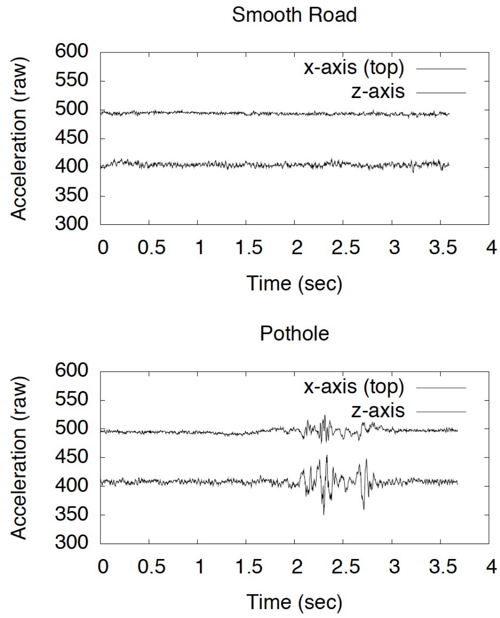


Fig. 1 Examples of acceleration data of detected smooth road and pothole [14].

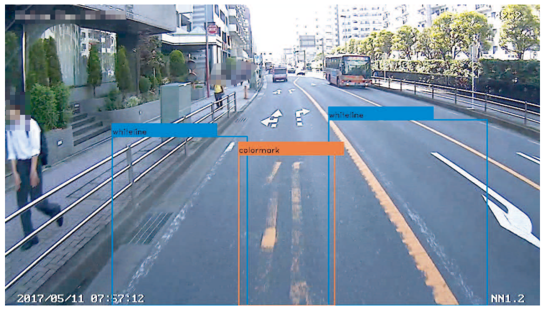


Fig. 2 Examples of detected blurred road markings [15].

driving conditions. In the work of [13], a stereo vision sensor and a laser range sensor are introduced to improve the location estimation accuracy. By sharing GPS data and distance data measured from range sensors among neighboring vehicles via V2V communication, a cooperative positioning system was proposed in [11] which reported via simulation that the proposed system improves the estimation accuracy by 85% on average with respect to the standalone GPS receiver, and recognizes about 70% surrounding vehicles with an error of $1m$.

Automotive sensing has also been widely used to detect the status of transportation infrastructure and traffic. The authors of [14] studied to detect pothole in road surface using accelerometer data measured by vibration sensors installed on taxis. **Fig. 1** shows the examples of acceleration data of detected smooth road and pothole, respectively. In a recent work of [15], the authors adopted CNN-based image processing to detect the blurred road markings from driving reorder videos as shown in **Fig. 2**. In [16], the authors studied an urban traffic monitoring system where vehicles act as mobile sensors to send traffic information they sensed to traffic-monitoring center for traffic status evaluation. In particular, a patrol mechanism was introduced to proactively participate in traffic monitoring. Two path-planning algorithms to controlling the path of patrol vehicles were proposed. Simulation

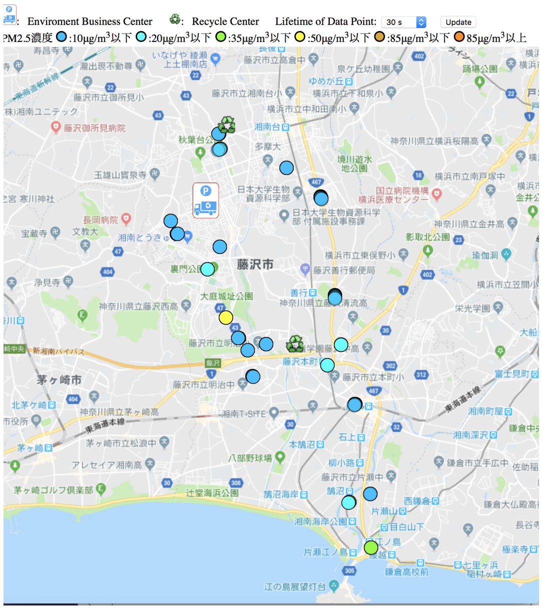


Fig. 3 A screenshot of the real-time PM2.5 concentration monitoring system Fujisawa, Japan. [27].

study showed that the proposed patrol control algorithms can significantly reduce estimation error compared with random patrol. Automotive sensing have also been used to find available parking locations [17–19], urban planning [20] and accident avoidance [21–23].

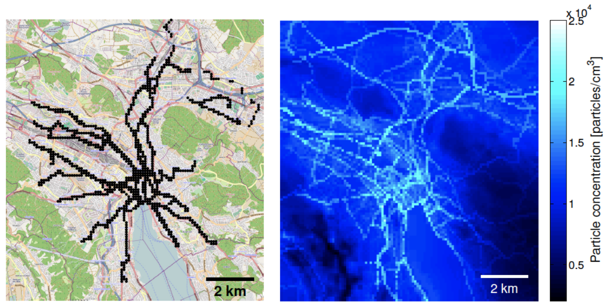
2.2 Environmental monitoring

While monitoring stations can be deployed to place of interests, it is usually impractical to deploy such stations densely to cover a whole city. On the other hand, microscope environmental measures are of more concerns from the view of citizens, so the automotive sensing has also been used to achieve a fine-grained environment monitoring in urban areas.

In the work of [24], the authors developed a prototype system to monitor the concentration of CO2 in a university campus, where the sensory data was delivered to data server(s) via GSM short message function. In [25, 26], the authors implemented air quality monitoring systems consisting of both mobile nodes and static nodes. Air quality sensors was installed into vehicles like buses acting a mobile monitor to collect air quality data as they move around. Static nodes serve as communication backbones which receive the air quality data collected from mobile node in their vicinity and then deliver the received to data server(s), e.g.,via GPRS service.

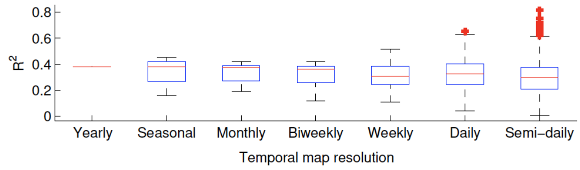
From the study of [24–26], we can observe that communication cost was one major obstacle to the development of the automotive sensing system. Due to the recent technology progress of cellular communication, the cost and data rate become acceptable eventually even if all the sensory data (excluding video streams) are delivered via cellular network. In [27], the authors equipped PM2.5 sensors into the door-to-door garbage collecting trucks of Fujisawa, Japan. 3G cellular communication was used to deliver the collected air quality data in real-time as shown in **Fig. 3**.

Besides communication, there still remain other topics that need to be further investigated in order to improve the data quality and usage. For example, compared with static stations, the vehicular sensors are of low accuracy. The measurements of static stations, which are typically accessible online, may be used for data calibration of the sensors mounted on vehicles. While the work of [28] proposed a framework, the design, implementation and evaluation of specific calibration schemes still remain an open area. Another topic is the generation of pollution map based on discrete measurements collected from the automotive sensing systems. In the work of [29], the authors applied regression models to predict the pollution levels for the locations without measurements as shown in **Fig. 4**. Evaluation results using a realistic data set showed that while reliable pollution maps with a high spatial resolution (less than 100m) can be obtained for yearly to monthly time scales, the predication errors grow sharply as temporal resolution increases (See **Fig. 5**). Therefore, how to generate spatio-temporal high-resolution virtualization maps using the environmental data obtained from automotive sensing remains an open research area.

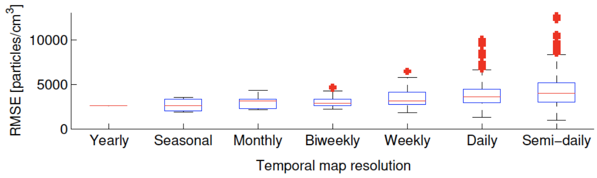


(a) Data coverage. (b) Pollution map.

Fig. 4 An example of pollution maps of Zurich, Switzerland [29].



(a) Coefficient of determination (R^2).

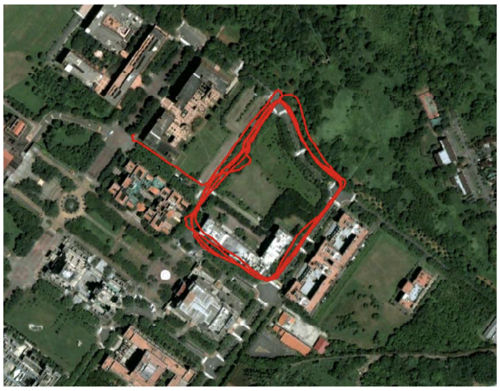


(b) Root-mean-square error (RMSE).

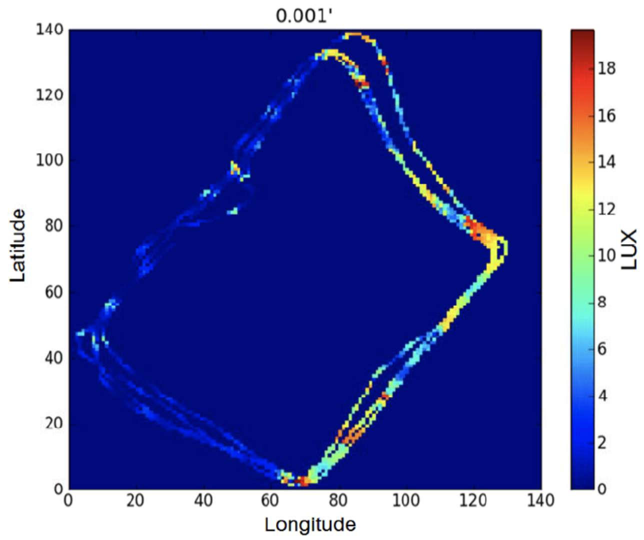
Fig. 5 Prediction errors increase sharply as the temporal resolution increases [29].

2.3 Object detection

In this section, we review the applications developed for collecting information regarding objects along roadsides. The idea of using automotive sensing for object detection is very intuitive. Since vehicles roam around over a whole city, the information regarding the objects of interests can be collected if we equip/extend the corresponding sensing equipments on the vehicles. Note that some object detection applications serve trans-

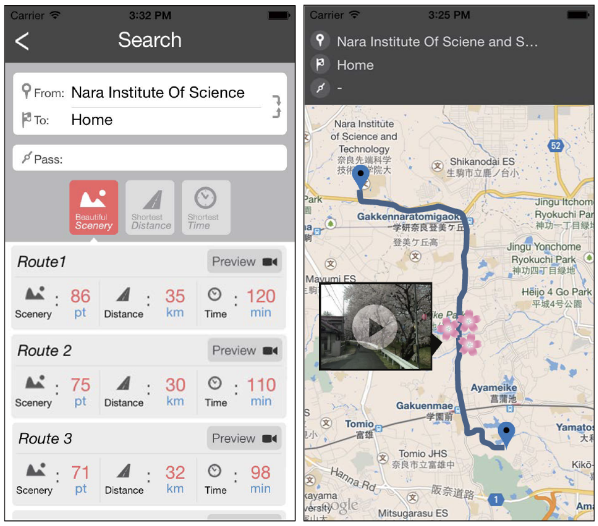


(a) The experiment path.



(b) The generated illuminance map.

Fig. 6 The illuminance map reported in [30].



(a) Route Selection View (b) Route Information View

Fig. 7 Detection and sharing the locations of good-view of cherry blossom along roadside [31].

portation systems, such like potholes and road markings. Those applications were included into the section 2.1.

The earliest work of object detection using automotive sensing we found in the literature is [30]. In the paper, the authors proposed a proof-of-concept system where illuminance sensors are equipped on commute buses for the generation of illuminance maps as shown in **Fig. 6**. Through the comparison between the current illuminance density and historical ones, the authors expected that locations of fault street lamps can be detected. While the concept proposed in [30] seems reasonable, the detection accuracy remains unclear because the implementation detail and performance evaluation were not elaborated.

Using the camera of smartphones mounted on vehicles, [31] proposed an interesting application that detects and shares the locations having a good-view of cherry blossom along roadsides as shown in **Fig. 7**. In [31], the authors applied histogram-based color analysis to quantify the density of the blossom in each frame and region-based fractal dimension analysis to alleviate mis-detection resulting from objects like building containing the similar colors to the blossom. The locations of targeted objects are often sparsely distributed and uncertain before detected, so it usually leads to waste of communication/computation resources. Based on this observation, a k-stage sensing scheme was proposed in [31] to improve the sensing efficiency. Under the scheme, a sparse sensing interval was set at first and places of interests (PoI), where detected objects are reported, are selected and shared among participated vehicles. Sensing intervals of the vehicles in the vicinity of the PoIs will be gradually narrowed until a predefined threshold is reached.

The aforementioned research including [15] discussed in section 2.1 demonstrate that automotive sensing is an appealing approach for the collection of various object-related information in urban areas. Besides, more and more vehicles are equipped with driving recorders, thus it is expected that recent progress of imaging processing technologies such as CNN-based object detection and tracking will inspire a lot of novel applications of automotive sensing technology. One possible challenge here is the detection accuracy resulting from insufficiency of data obtained from a single vehicle. This can be for many reasons, such as the steering angles of camera, noisy due to high velocity or obstacle of neighboring vehicles. Collaboration schemes among participated vehicles and data fusion from the independent measurements can be interesting directions to improve the detection accuracy in this area.

2.4 Platform

In this section, we review the existing platforms where a variety of sensors, vehicular devices, back-end server(s) and related softwares are developed to implement an urban sensing infrastructure rather than serving one specific application exclusively.

2.4.1 CarTel

The CarTel developed by MIT in 2006 is the seminal automotive sensing platform we found in the literature [6, 32]. The CarTel is designed to be an open programable platform where new kinds of sensors and heterogeneous data can be easily integrated and delivered via variable and intermittent network connectivity. As shown in **Fig. 8**, CarTel consists of three components: a *portal*, *ICEDB* (intermittently connected database), and *CafNet* (carry-and-forward network). The portal is deployed in

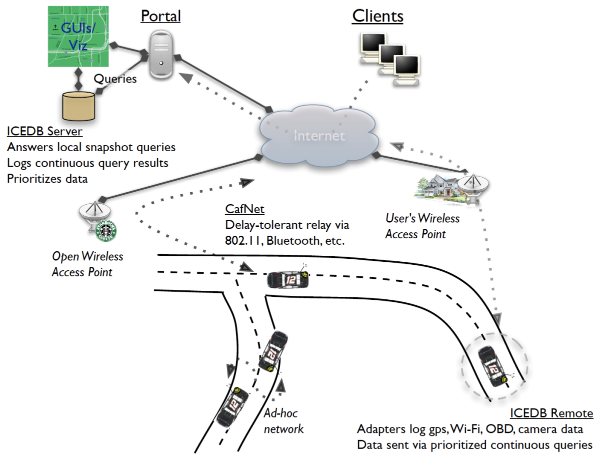


Fig. 8 The system architecture of CarTel [6].

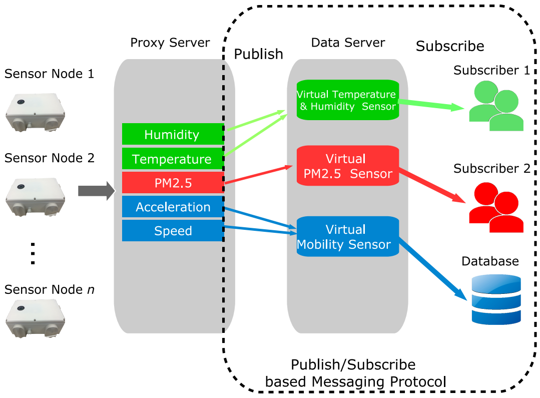


Fig. 9 The publish/subscribe data flow of Cruisers [27] .

back-end servers and acts as the control and configuration center as well as the sink node of the system. The function of ICEDB is to distribute query execution and return the corresponding response between the ICEDB server running on the portal and the ICEDB remote running on vehicular nodes. The delivery of messages between the server and vehicular nodes are implemented via *CafNet*, a network stack for carry-and-forward communication upon a intermittently-connected network. A small-scale experiment system consisting of six cars was implemented for validation.

2.4.2 Cruisers

The Cruisers is an automotive sensing system developed by Keio University and deployed in Fujisawa for the collection and realtime sharing of a variety of urban data starting from 2015 [27, 33]. The Cruisers is implemented in publish/subscribe pattern using an XMPP-extended message exchange server as illustrated in **Fig. 9**. 3G cellular network is adopted for communication, so that the collected sensory data can be published from vehicular nodes to back-end servers in a temporal scale of several hundreds of milliseconds [27]. A consumer of the data can obtain realtime data stream by subscribing to the virtual nodes of his/her interests. It is worthy to mention that by 2017, 66 door-to-door garbage collecting trucks have been included into the system as host vehicles, leading to a good coverage on the city as shown in **Fig. 11**.

A comparison between CarTel and Cruisers was summarized

Fig. 10 The reconstructed path in one experiment test [34]. The numbers represent the estimated distances. Those in parentheses are the actual corresponding distances.

in **Table 1**. From Table 1, we can make the following observations. First, the evolution of wireless technology like cellular network not only provides a widely accessible, low-delay and high-rate communication service but also reduces the complexity in the development and deployment of automotive sensing platforms. Second, publish/subscribe should become a dominant mode in future automotive sensing platforms because it provides a unified yet flexible and data-driven API for application development. We also notice that the DTN stack adopted in CarTel provides a degree of network failure-resilience. Therefore, the development of disaster-resilient automotive sensing systems can be a promising direction.

2.5 Others

In this section, we review the interesting and inspiring applications of automotive sensing that do not belong to the above categories.

In [34], the authors proposed a system called AutoWitness to deter, detect, and track personal property theft. In particular, a tag is attached to an asset to be protected, where the tag remains in sleep until vehicular movement is detected, assuming that the thief is moving the asset via a vehicle. Once movement is detected, the tag uses inertial sensor-based dead reckoning to estimate and record position changes including moving distances between turns and/or stops. The recorded data will be delivered to a back-end server via cellular communication, in which the moving path can be reconstructed using a hidden Markov model as shown in **Fig. 10**. A detailed evaluation on the errors of movement detection and distance and turn estimations were conducted in [34], showing the feasibility of the proposed system.

3. Sensing Quality Evaluation

While the mobility of vehicles helps to improve the spatial coverage of the mounted sensors of automotive sensing systems in general, it also introduces novel challenges in the evaluation of the sensing quality for smart cities. In this section, we review the existing preliminary but insightful attempts in the literature where novel metrics are proposed for the sensing quality evaluation of automotive sensing system.

In [35], the authors focused on the construction of 2D sensing maps for environment monitoring applications and proposed a metric called *urban resolution* to measure the sensitivity of automotive sensing systems based on imaging signal processing tech-

Table 1 A comparison between CarTel [6] and Cruisers [27].

Platform	Communication	Data publishing mode	Realtime publishing	Experiment scale	Temporal sampling rate	Integrated sensors
CarTel	WiFi or bluetooth with unreported link rate	Query/Response	No	6 vehicles	Up to 1Hz	GPS, WiFi status, OBD-II, speed, acceleration, camera
Cruisers	3G cellular network with up to 100bps per link	Publish/subscribe	Yes	66 vehicles	Up to 100Hz	Acceleration, Angular Velocity, Geomagnetism, Atmospheric Pressure,Temperature, Humidity, UV-A, Illumination, PM2.5, GPS

niques. Concept validation based on both mobility and realistic data sets are conducted in [35] to demonstrate the usage of the proposed metric. The readers are referred to [35] for more details of the definitions with regard to the metric.

Notice that the service quality of automotive sensing is not only affected by the spatial distributions of vehicles but also by the temporal dynamics. Inspired by this observation, the work of [33, 36] studied novel sensing coverage metrics in both spatial and temporal dimensions. In [36], the authors introduced a metric, ICT *Inter-Cover Time*, which is defined as the time elapsed between two consecutive coverage of a sensing target. Based on the distribution of ICT, a metric called *opportunistic coverage ratio* is proposed and calculated as the ratio of expected expected ratio of covered objects over the whole sensing space in a given interval. Evaluation based a cell-partitioned map realistic trajectory traces was conducted in [36]. The evaluation result reported that the aggregated ICT distribution follows a truncated power-law distribution. The work of [33] focused on worst-case performance guarantees and proposed a metric called t-coverage that denotes the set of sensing objects that can be covered (i.e., sensed) at least once in any arbitrary time interval t. The usage of the proposed metric was demonstrated using realistic trajectory traces of Cruisers as shown in Fig. 11.

While the aforementioned studies proposed interesting ideas and obtained insightful results, the quality evaluation for automotive sensing remains unexplored including but not limited to the following aspects. First, the distribution spaces of targeted sensing objects are diverse. For example, in the object direction-related applications, the targeted sensing objects are discrete points distributed in a one-dimension space, while in the environmental monitoring, the final aim is to generate a two-dimensional map based on discrete sample measurements. Second, even in a specific application, the distribution of the sensing object(s) can be different in temporal and/or spatial dimensions. For example, the air pollution level in a metropolitan area may vary more dynamically and thus requires a higher sampling rate than those for a rural countryside. The work of [33, 35, 36] relies on cell-partition approaches. Advanced evaluation methods to addressing the challenges discussed above can be an extremely promising research direction.

4. Conclusion

In this survey, we reviewed recent progress in the applications of automotive sensing to realize the vision of smart cities. It is expected that this report will serve as a guidebook to those who want to apply automotive sensing in their development of smart cities-related applications. The limitations of existing work as well as possible future directions were also discussed. We wish our viewpoints will encourage and help researchers to further advance the study of automotive sensing in future.

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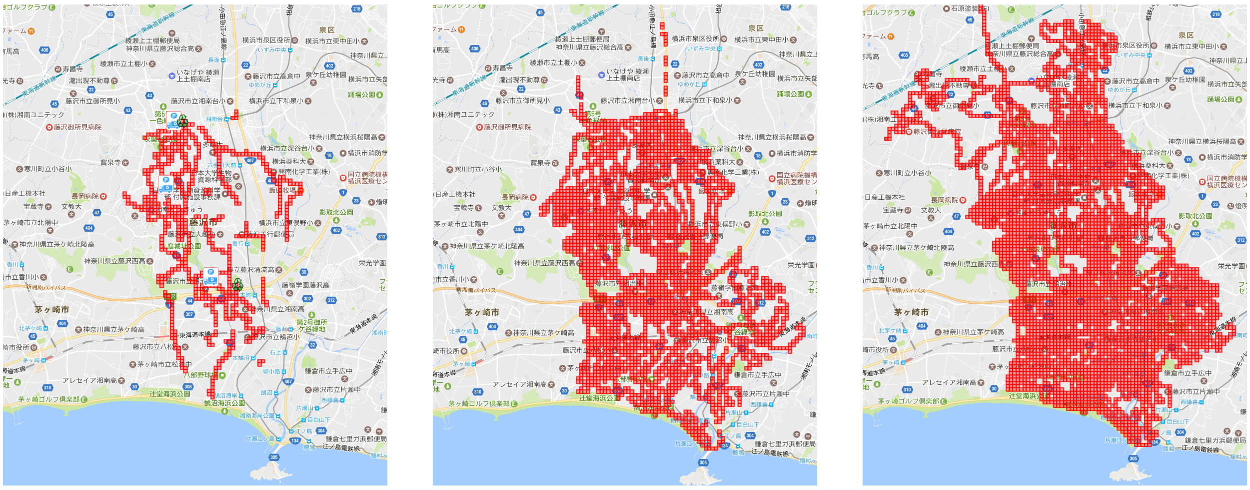

(a) 1 day-coverage. 9.7% of the city region are covered.

(b) 2 days-coverage. 41.9% of the city region are covered.

(c) 3 days-coverage. 64.5% of the city region are covered.

Fig. 11 Spatio-temporal coverage of Cruisers [33]. The size of a cell is set to $100m \times 100m$.

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