City Scanner: Building and Scheduling a Mobile Sensing Platform for Smart City Services

Amin Anjomshoaa, Fábio Duarte, Daniël Rennings, Thomas Matarazzo, Priyanka deSouza, and Carlo Ratti

***Abstract*—A large number of vehicles routinely navigate through city streets; with on-board sensors, they can be transformed into a dynamic network that monitors the urban environment comprehensively and efficiently. In this paper drive-by approaches are discussed as a form of mobile sensing, which offer a number of advantages over more traditional sensing approaches. It is shown that the physical properties of the urban environment that can be captured using drive-by sensing include Ambient Fluid, Electromagnetic, Urban Envelope, Photonic, and Acoustic properties, which comprise the FEELS classification. In addition, the spatiotemporal variations of these phenomena are discussed as well as their implications on discrete-time sampling. The mobility patterns of sensor-hosting vehicles play a major role in drive-by sensing. Vehicles with scheduled trajectories, e.g., buses, and those with less predictable mobility patterns, e.g., taxis, are investigated for sensing efficacy in terms of spatial and temporal coverage. City Scanner is a drive-by approach with a modular sensing architecture, which enables cost-effective mass data acquisition on a multitude of city features. The City Scanner framework follows a centralized IoT regime to generate a near real-time visualization of sensed data. The sensing platform was mounted on top of garbage trucks and collected drive-by data over eight months. Acquired data were streamed to the cloud for processing and subsequent analyses. Based on a real-world application, we discuss and show the potential of using drive-by approaches to collect environmental data in urban areas using a variety of non-dedicated land vehicles to optimize data collection in terms of spatiotemporal coverage.**

***Index Terms*—Environmental monitoring, Mobile sensing, Mobility patterns, Road vehicles, Smart city, Spatiotemporal phenomena, Urban areas, Wireless Sensor Networks.**

I. Introduction

CITIES are data factories; enormous amounts of data are generated from various sources, every day. Increasing efforts to collect such data from the urban environment are driven by promises of improved services or products for the public, ranging from self-driving cars, to smart buildings, and data-driven traffic lights. Collections of spatiotemporal datasets of urban phenomena can thus empower advanced analytics and technical solutions for local governments and urban planners.

Recently, portable sensors, with high accuracy and embedded communication technologies, have become available and affordable. A number of studies have utilized vehicles to carry such sensors with the aim of capturing a specific feature of the urban environment, e.g., air quality [3], [20] or road conditions [36]. One of the most commonly used terms in the vehicular-based sensing paradigm is Vehicular Sensor Networks (VSNs), in which vehicles have a certain role in a Wireless Sensor Network (WSN). In this paper, we adopt the term drive-by sensing to refer to urban sensing using road vehicles.

Drive-by sensing offers a number of advantages over more traditional approaches, such as remote and stationary sensing. Natural phenomena and physical properties are typically continuous signals in both temporal and spatial dimensions. To represent these signals as digital sensor data, each sensing channel must capture sufficiently dense spatiotemporal data for its application. Yet, in many environmental use-cases, the collected data have been constrained in spatial and/or temporal dimensions, which limits the information that can be extracted. For instance, stationary air pollution sensors measure the ambient pollutants in precise locations, but miss potential differences in nearby streets and neighborhoods [34]. On the other hand, satellite-based measurements can be used to infer air quality levels over large swaths of land, but are sampled infrequently. Moreover, robust mathematical models are required to predict more detailed changes in surface temperature over time [30]. These methods have however been shown to be accurate for certain applications that do not require a high temporal resolution, such as measuring chlorophyll concentration in coastal zones [9].

This paper introduces *City Scanner*, a mobile sensing platform for smart city services. Related works in drive-by sensing are discussed in Section II. Subsequently, a general categorization of spatiotemporal phenomena that can be captured in a drive-by approach is introduced in Section III. In Section IV, the sampling characteristics of drive-by sensing methods are discussed and compared with airborne and stationary sensing. Since City Scanner is specifically created to be deployed on a fleet of existing vehicles, the suitability of various vehicles in terms of spatiotemporal coverage is addressed in Section V. The ideology of the paradigm is furthermore elaborated upon in Section VI. As a proof of concept, City Scanner has been deployed on municipal garbage trucks in Cambridge, MA for eight months. The outcomes and implications of this application are discussed in Section VII. Finally, we conclude our work in Section VIII.

II. Related Works

In the domain of VSNs, a number of studies have focussed on the network architecture and communication aspects, leading to many publications on vehicle interactions

The authors are with the Senseable City Laboratory, Massachusetts Institute of Technology, Cambridge, MA, USA e-mail: {amina, fduarte, rennings, tomjmat, desouzap, ratti}@mit.edu.

Fábio Duarte is also with Pontifícia Universidade Católica do Paraná, Brazil.

Daniël Rennings is also a MSc student at Delft University of Technology, the Netherlands.

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TABLE I
OVERVIEW OF DRIVE-BY SENSING STUDIES

Title	Urban Phenomena	Utilized Sensors (* is from smartphone)	Type of Vehicle
CarTel [11]	Traffic congestion, WiFi access points, driving behavior	GPS, WiFi, OBD, camera	Car
BikeNet [4]	Passing vehicles, cycling behavior, topography, air quality, noise pollution, visual map	GPS, 2-axis accelerometer, CO_2 meter, reed relay, camera*, microphone*	Bike
Nericell [24]	Road quality, traffic conditions	Accelerometer*, microphone*, GPS*	Car
ParkNet [19]	Parking statistics	GPS, ultrasonic rangefinder	Car
VOTERS [36]	Road conditions	GPS, camera, microphone, accelerometer, mm-wave radar, GPR, tire pressure sensor	Van
N.A. [14]	Street lighting infrastructure	GPS, light sensor, CCD Camera, odometer interface, IMU, OBD	Van
N.A. [29]	Thermal signature	GPS, long wave infrared radiometric cameras, near-infrared camera, optical camera	Van
N.A. [1]	Air pollution	GPS, NO, NO2, black carbon	Google Street View vehicles

in terms of communication [33]. The prohibitive costs and privacy implications of real field experiments with hundreds of instrumented vehicles envisioned in these scenarios, has forced researchers and developers to fall back to simulations [8]. On the other hand, much less attention has been given to research that has utilized a fleet of non-interconnected ground vehicles as a resource for monitoring the environment, which was previously referred to as drive-by sensing. An overview of drive-by sensing studies, with their respective configurations and sensing purposes is presented in Table I.

A little over a decade ago, drive-by sensing emerged as a new network paradigm for sensing urban environments [15]. One of the first works in this domain, [11], already envisioned the paradigm would prosper in cases where the individual sensors are costly or the number of required sensors is so large that a stationary deployment is impractical. However, the need for high computation power and high storage space used to make potential costs for network deployment and maintenance relatively high [22]. Early works had to do concessions, such as prioritization and aggregation of measurements, due to the fact that sensors produced more data than the system could promptly deliver to the back-end [11]. The recent availability of affordable and portable sensors and ubiquitous smartphones with advancing sensing capabilities [28] have bolstered to this platform in terms of sensing opportunities, communication possibilities, and cost-effectiveness. However, in recent studies, the limit of GPS accuracy was sometimes a problem. Employed solutions include utilizing additional data (from e.g. IMU or on-board diagnostics - OBD) and methods to cope with noise such as a Kalman filter (e.g. [14]), snapping data to a set of closest fixed locations (e.g. [1]) or utilizing environmental fingerprinting (e.g. [19]). A similarity between the early and latest studies is the usage of a modular, expansible sensing architecture.

Drive-by sensing configurations can be categorized as being either multi- or single purpose. In a multi-purpose setting, the sensor network is designed to simultaneously capture several city features for multiple purposes; so far, three studies fall under this classification [11], [24] and [4][1]. In the single purpose case, the focus is on a single urban phenomenon, although multiple sensors may be utilized.

Drive-by sensing has been employed to measure city features ranging from natural phenomena such as temperature, humidity, and air quality, to those more closely related to the urban environment, e.g., parking spot occupancy, street light infrastructure, road conditions, traffic congestion, and WiFi access points. However, the majority of efforts are focused on quantifying air quality and road conditions in urban environments[2]. The works on air quality often include meteorological measurements, predominantly being temperature and humidity, to correct the raw measurements for the effect of environmental parameters using a calibration mechanism (e.g. [13], [21]). Studies on road quality have utilized IMUs in smartphones (e.g. [24]), microphones (e.g. [23]), or a combination of dedicated hardware (e.g. [36]). The most prevalent application of vehicle-based sensing is Google Street View[3], but we can also find applications such as assessing and optimizing a lightning infrastructure [14] and mapping cyclist experiences [4]. Apart from new applications, the value of this paradigm is underlined by multiple orders of time reduction (e.g. [36]), cost reduction (e.g. [29]), and increase in spatial precision (e.g. [1]) compared to traditional methods for capturing urban phenomena.

Generally, drive-by sensing employs cars (e.g. [11]) or vans (e.g. [16]); although other vehicles, such as bikes [4], buses [6], and taxi cabs [10], [5], have been utilized. The majority of drive-by sensing deployments used dedicated vehicles, which were driven solely for data collection purposes. Some of these packages can be set up on an existing fleet of vehicles, but the suitability of each vehicle type is yet to be studied in detail[4]. Vehicle modifications are sometimes also required in drive-by applications: a car window must be open in [14] and [19] and a bike is almost completely covered with sensors in [4]. Such adjustments may restrict the scale of the deployment. Some studies have utilized lab-grade sensors [1], whereas others employed cheaper sensors [19] or smartphones [24].

[1]Other studies, such as [2] and [31] do not fall under this category; although a prototype was established, a deployment for urban data collection was not presented.

[2]Table I contains some advanced works, however different from related works such as [35], [6], [5], and [24], they use more expensive sensors, and more often use dedicated vehicles

[3]See https://www.google.com/streetview/.

[4] [7] studied different vehicles, although their focus is on a difference in (e.g. IMU) signals per vehicle while crossing the same road.

Furthermore, some vehicles have been employed to acquire hundreds of hours of data (e.g. [1]), whereas others have just been used to collect a small dataset of several hours of data [24]. The majority of works also includes a visualization of their data, although most lack to show a temporal dimension to the user.

In the *City Scanner* project, a portable, self-contained general-purpose sensing platform is deployed on top of existing garbage trucks, such that the hosting vehicle is practically unaltered. The initial data from an 8-month deployment allows a user to explore both the spatial and temporal dimensions of the scheduled data collection.

III. Sensor Types and Potential Applications

Today, with the rapid advances in sensor technology, there is a handful of sensors that can be used to monitor and capture various physical aspects of the external environment such as light, temperature, humidity, magnetic fields, and sound. In this context, we introduce FEELS as a general classification for these urban properties to organize the vast amount of opportunities that lie in drive-by sensing. Focusing on drive-by sensing, an overview of typical sensor types and their corresponding urban applications are provided per property type in Table II.

A. Fluid (Ambient Fluid Properties)

The ambient fluid in both the air and water include particulates, chemical substances, and biological molecules. The ambient air use cases are most relevant to City Scanner, as it uses land vehicles, hence Table II is limited to these use cases. The most common application in this category is air quality monitoring.

B. Electromagnetic Properties

Urban areas include an increasing number of electronic devices which emit an agglomeration of radio waves and electromagnetic fields in urban areas. These radio waves, similar to visible light and infrared radiations, are part of the electromagnetic spectrum and have wavelengths longer than infrared light.

C. Envelope (Urban Envelope Properties)

This group of physical properties includes the built environment (e.g. buildings, street surfaces, the subsurface infrastructure), as well as the interactions between vehicle and its surroundings (e.g. acceleration). Accelerometers, ultrasonic sensors and LIDAR sensors are examples of sensors that can capture parts of the urban envelope. Recently, these types of sensors have been included in self-driving applications to provide the vehicles with comprehensive information about their surroundings [26]. As such, autonomous cars can interpret the roads correctly as they drive.

D. Light (Photonic Properties)

Multi-spectral light sensors are used to capture the infrared and the visible regions of the electromagnetic spectrum. In the case of autonomous vehicles, multi-spectral imaging has applications in navigating through the built environment. Infrared imaging has also been helpful for some use cases beyond thermal efficiency, for instance, the detection of methane gas leaks [25].

E. Sound (Acoustic Properties)

The acoustic properties of an urban environment are influenced by urban factors such as various noise sources and acoustic propagation effects. Such factors can be used to identify human activity patterns and the distribution of noise pollution over time in various urban areas.

IV. Density Requirements of Spatiotemporal Phenomena

In the case of mobile sensing, the usefulness of the data roughly depends on the number of captured data points in a specific spatiotemporal area. However, the required number of points varies according to the phenomenon under study[5]. For instance, we would need a high spatial density of data points for capturing noise, whereas temperature in urban areas can be captured with a lower spatial density. On the other hand, the street surface quality is much less sensitive to time compared to e.g. air pollution.

A. Methods of Sensing

Common sensing techniques do not cover urban areas effectively in space and time. Generally, airborne sensing covers large areas of target cities at sparse time intervals, whereas stationary sensors have a high temporal coverage, but capture signals at one point in space. Drive-by sensing can overcome some of the limitations of stationary and remote sensing approaches.

However, urban phenomena are not strictly bound to one category. For instance, air pollution can be measured through satellite images, drive-by sensing or stationary sensors. The difference in such measurements is the spatiotemporal coverage for the target area and given time window. Also, the practical constraints of these approaches are not explicitly defined. In the case of air quality, a larger fleet of satellites or larger network of stationary sensors can be employed to respectively acquire a higher temporal and spatial coverage, but a drive-by approach may be more cost effective instead. Though, the latter also faces constraints: it is limited in time due to cost of deploying a large fleet of mobile sensors, and in space as it is confined to a street network.

As an example consider the use cases of greenery or parking spot identification. Greenery mapping can be achieved by analysis of satellite images or with more novel approaches that benefit from drive-by images [17]. Likewise, parking

[5]The application of the obtained data also plays a significant role that is generalized here to common applications such as identifying air pollutant hot spots, potholes and urban heat islands.

TABLE II
OVERVIEW OF SENSORS AND APPLICATIONS FOR FEELS PROPERTIES

Type	Sensor	Potential Applications
Ambient Fluid	Particulate matter	• Monitoring the distribution of fine particulates (e.g. PM2.5, PM10)
	Chemical pollutants: CO_x, NO_x, SO_x, O_3	• Monitoring the distribution of various pollutants
	Methane sensor	• Detecting methane leaks
	Nanosensors (no commercial sensors yet)	• Detecting explosive material • Detecting chemical substances
	Temperature, Humidity, Air pressure	• Monitoring urban heat island phenomena
	Particle radiation	• Monitoring the airborne particulate radioactivity
Electromagnetic	WiFi, Bluetooth	• Crowd and station mapping by scanning WiFi and Bluetooth signals
	GPS	• Localization and annotating sensor data • Inferring mobility aspect of vehicles (e.g. mobility mode of people or traffic status)
	RFID scanner	• Tracking and managing assets in urban areas (e.g. trees) • Sensing of spatial information by implanted beacons (e.g. road conditions)
	Isotropic sensors, Magnetometers	• Monitoring the electromagnetic field level (e.g. for studying irradiation impacts on citizens)
Urban Envelope	LiDAR, Ultrasonic	• Generating 3D model of cities • Monitoring the street surface quality • Monitoring road-side parking spots
	Wave Radar, Ground Penetrating Radar	• Monitoring the street surface quality • Identifying the pavement material and quality • Detecting black ice formation • Mapping the subsurface infrastructure (e.g. pipes, cables, tunnels)
	Accelerometer, Gyroscope, Odometer	• Monitoring the street surface quality • Monitoring road traffic and identifying hazardous road segments • Monitoring driving behavior • Monitoring bridge vibrations
Photonic	Visual camera	• Real-time imaging of urban areas and creating panoramic views • Monitoring of crowd and vehicles for event management and security purposes • Monitoring of traffic
	Thermal camera	• Monitoring energy efficiency of built environment • Monitoring the anthropogenic heat pollution • Detecting natural gas and CO2 emissions • Monitoring crowd • Monitoring infrastructure (e.g. powerlines, street surface) • Detecting black ice formation
	Photosensor	• Monitoring street lightning infrastructure quality, blazing light and reflections
Acoustic	Audio sensor, Microphone	• Monitoring noise and identifying activity patterns • Mapping the soundscape of cities • Monitoring the impact of noise controlling measures (e.g. noise-absorbtion walls)

spots can be identified by a network of stationary parking sensors or, more efficiently, via a drive-by approach [19]. Fig. 1 illustrates key coverage attributes of various sensing approaches in terms of time-sensitivity and space-sensitivity of target urban phenomena, as well as the cost barriers for each category.

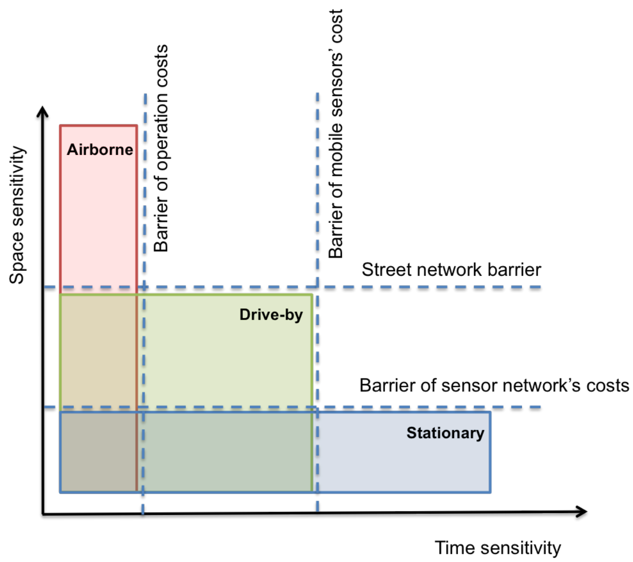


Fig. 1. Illustration of spatial and temporal coverage of airborne sensing, drive-by sensing, and stationary sensing; each technique has constraints in space and time. Drive-by methods offer a midrange mixture, which is adequate for observing multiple city features in a way that is not cost-effectively achievable by the other means.

B. Sampling Resolution

There is a fundamental relationship between the vehicle speed, sampling rate, and spatial resolution, which should be considered for each channel in the design of an urban mobile sensing platform. For simplicity, consider the scanning of a one-dimensional segment of length, L, using one vehicle at a constant speed, v, and temporal sampling rate, F_s. The corresponding spatial resolution is $\Delta r = \frac{v}{F_s}$ and defines the tradeoff between data density and vehicle speed for a given sensor sampling rate. Whereas a constant vehicle speed is impractical in an urban setting, the sampling properties of the sensing channels can be designed conservatively based on maximum values. Finally, Nyquist-Shannon sampling theorem applies simultaneously in time and space [12]. The highest temporal and spatial frequencies that may be reconstructed are $f_{t,Nyq} = \frac{1}{2\Delta t}$ and $f_{r,Nyq} = \frac{1}{2\Delta r}$, respectively, where $\Delta t = \frac{1}{F_s}$.

V. Mobility Patterns of Hosting Vehicles

Whereas the majority of drive-by solutions have used dedicated vehicles to gather data from the environment, the City Scanner approach exhibits existing fleets of vehicles that cover the urban areas in a regular basis. However, the route for data collection is in this case defined by the hosting vehicles. For this reason, it is important to understand that apart from the sensing frequency, the spatiotemporal coverage of scheduled and unscheduled urban vehicles play a major role in City Scanner. These coverages are further discussed next.

A. Scheduled Vehicles

City-owned vehicles such as buses and trash trucks can be used to carry sensors around the city. Although both vehicles use predefined routes and schedules, their mobility patterns are very different. Bus lines cover predefined routes, which consist of a fixed number of street segments, many times per day; whereas trash trucks cover a larger number of street segments but operate for fewer hours (e.g. morning or night hours) per day, and usually operate only a few days a week in each zone. Fig. 2 illustrates the differences between coverage pattern of bus lines and trash trucks.

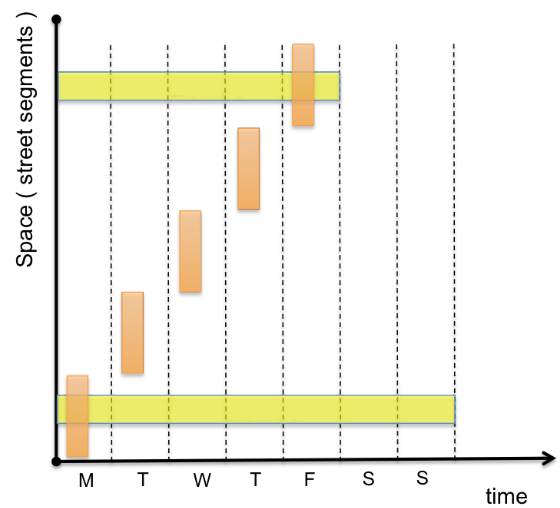


Fig. 2. Street segment coverage using mobile sensors on buses (yellow boxes) versus trash trucks (orange boxes).

For instance, in Cambridge, MA, the trash trucks run between 7:00 am to 2:00 pm and during this time, each truck covers on average 133 out of 2615 street segments. The total number of street segments that are covered by trash trucks is 1,739, which is around 67% of street segments[6]. On the other hand, the longest bus line in Cambridge covers less than 1% of street segments, but it covers those segments many times per day. Fig. 3 depicts the bus lines in Cambridge and the percentage of street segments covered by each line[7] as well as their corresponding number of trips.

B. Unscheduled vehicles

Other kinds of urban vehicles, such as taxis, do not follow predefined schedules. Although these vehicles exhibit some spatial and temporal mobility patterns, their behavior is less systematic compared to buses and trash trucks. Without further knowledge, it can be assumed that these vehicles follow stochastic mobility patterns. Therefore, the number of data

[6] Some areas of Cambridge are dedicated to university campuses and are not covered by the municipal trash trucks

[7] Based on the open data feeds of Cambridge's transportation authority, see https://www.mbta.com/developers.

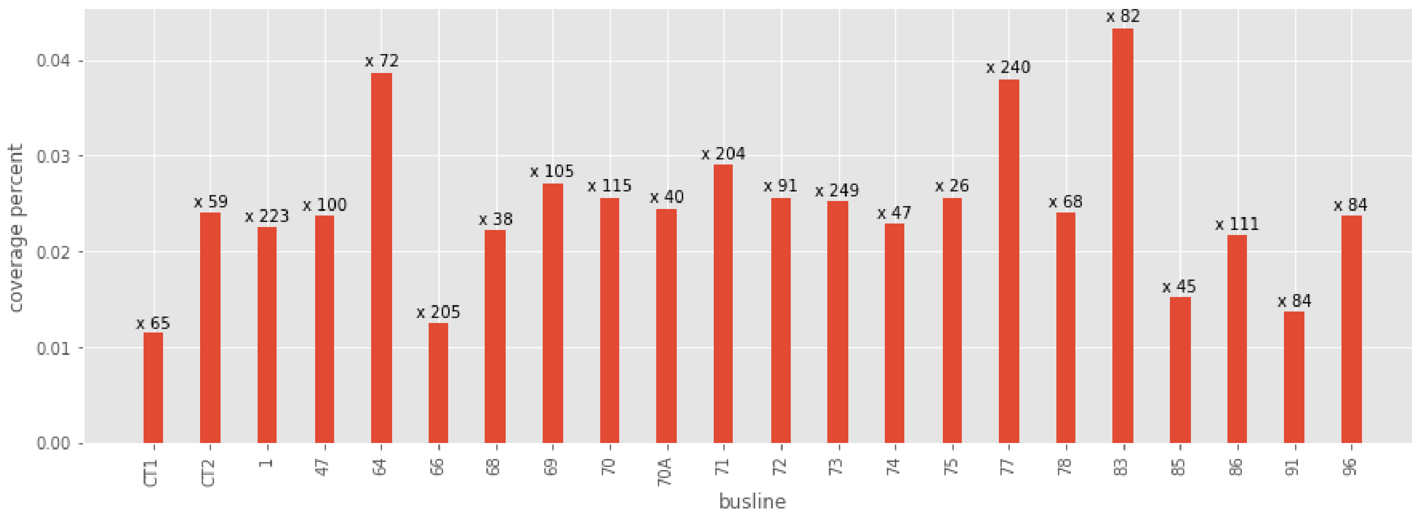


Fig. 3. Percentage of street segments covered by bus lines in the City of Cambridge during weekdays. The numbers above columns are the number of daily trips along the respective segments

points within a specific area (e.g. street segment) and a time window, would also be stochastic. Fig. 4 shows the mobility patterns of such vehicles that provide a stochastic spatiotemporal coverage for selected area and time window. In this context, the spatiotemporal coverage is expressed as the number of measurements inside the green box.

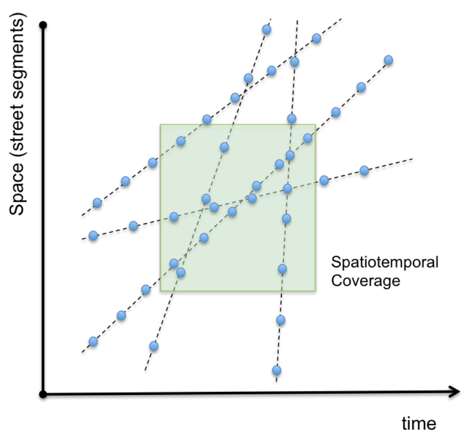


Fig. 4. Example of random mobility patterns and their corresponding spatiotemporal coverage of a selected area

To demonstrate the coverage of sensors deployed on vehicles such as taxis, an open dataset of taxi trips from Manhattan, in New York City[8] was analyzed. In Manhattan, there are around 7,500 street segments and the selected dataset (year 2011) contains around 140 million trips of more than 13,000 taxis. For this analysis, subsets with different sizes (5 to 100 taxis) were randomly selected. The number of daily visits of street segments was calculated for each group. In addition, for each sample size, the experiment was repeated five times for verification.

Fig 5, depicts the results of this analysis and demonstrates that by equipping only five taxis, around 30% of street segments in Manhattan will be visited at least once per day. With 30 taxis, the number of street segments covered at least once a day increases to around 60%, and half of these segments get more than four visits per day. It is interesting to note that the longest bus line in Manhattan visits about 5% of all street segments, although this configuration would result in guaranteed measurements of the target street segments in both the temporal and spatial domain.

[8]See http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml.

VI. City Scanner Framework

City Scanner was introduced as a self-contained general-purpose sensing platform that exhibits an existing fleet of vehicles, without interfering with their operations. In this section, we elaborate upon the framework that establishes these features, which is displayed in Fig. 7.

City Scanner follows a centralized IoT regime to generate a near real-time map of sensed data. The individual sensing units are mounted on top of urban vehicles to record data and stream it to the cloud for processing and analysis. The core components of sensing units include power management, data management, and cloud streaming components (see Fig. 6). Since all components are encapsulated in the portable sensor platform, no additional resources (such as power or an open window) are required other than some surface area on the bodyshell. Also, this configuration allows advanced features, such as energy self-sufficiency, to be readily incorporated. Apart from these core components, sensor nodes are designed in a modular way so they can be added or removed to build different sensing configurations. In the case of city-owned vehicles, this solution thus gives cities (which own, manage or regulate such fleets) the power to decide which and how many sensors to deploy to acquire the data they need for specific applications. These possibilities come at no other cost than the hardware, while being less intrusive than any related work.

The quantity of sensors deployed in the platform is only limited by practical constraints such as power consumption, network reliability, and local processing capacity. The sensor

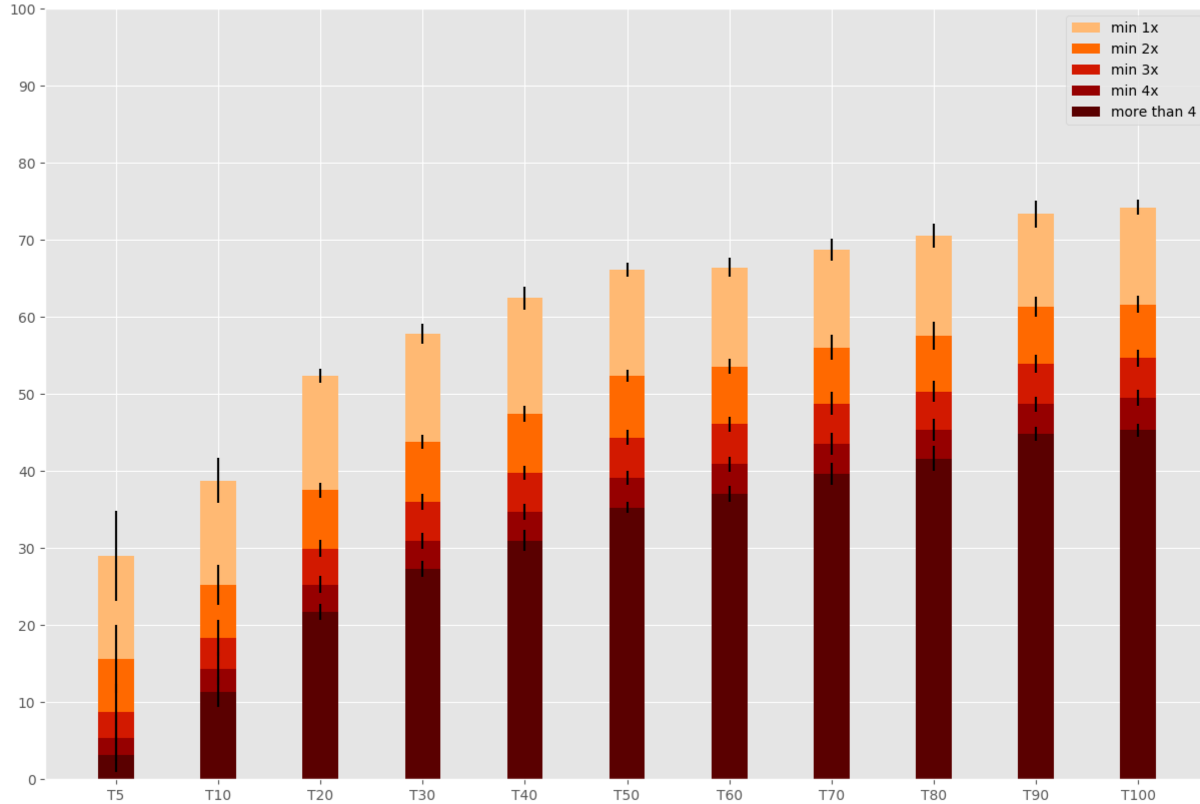


Fig. 5. Coverage of street segments by groups of randomly selected taxis in Manhattan, New York City on March 18, 2011

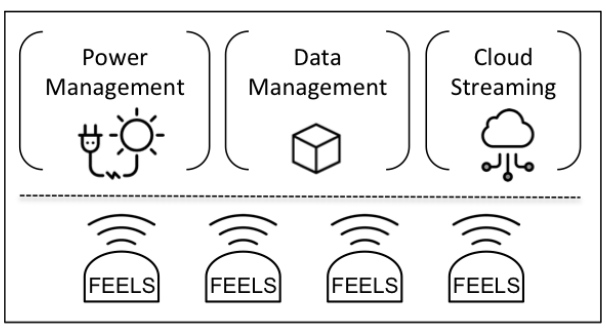


Fig. 6. City Scanner sensing unit with FEELS sensor nodes

nodes and the core unit will be deployed on one hosting vehicle and communicate via a short-range WiFi network which is used to send the captured data to the core unit for preliminary analysis and streaming to the cloud based on the power restrictions and availability of the network. Since the City Scanner platform uses standard Transmission Control Protocol (TCP) for data transfer, the data is reliably transferred from sensor nodes to the core component, as well as from the core component to the cloud.

On the cloud, each type of sensor data will have a number of corresponding services that can be used to design a data processing pipeline. These services can range from simple data storage, filtering, and visualization to more complicated services such as data analytics and machine learning.

VII. Trash Truck Experiments

The first deployment of City Scanner was conducted in cooperation with the Department of Public Works, City of Cambridge, MA, United States. To this end, we have employed a set of non-intrusive sensors including thermal cameras, WiFi scanners, accelerometers, GPS, and air quality, temperature, and humidity sensors. The sensors were deployed on trash trucks (see Fig. 8) that cover the entire area of the city on a weekly basis. Since the trash trucks are following predefined routes, we have been able to scan the same area every week and over time the captured data has generated a unique signature for each street segment.

The captured data consists of over 1.6 million measurements and could - if needed, in combination with other data sources - be used for various purposes such as analyzing the thermal efficiency of building façades, detection of certain infrastructural failures (e.g. the overheating of power lines), studying thermal pollution/heat-island phenomena in urban areas, and studying the impact of microclimate on pedestrian comfort. With the results of the current 8-month deployment of City Scanner, thermal abnormalities and air pollutant hot spots could be identified utilizing known methods that were customized to process drive-by data. In the following we discuss processing methods that have been applied on the thermal image and air quality data to enable such analyses and elaborate upon the challenges faced in the trash truck deployment.

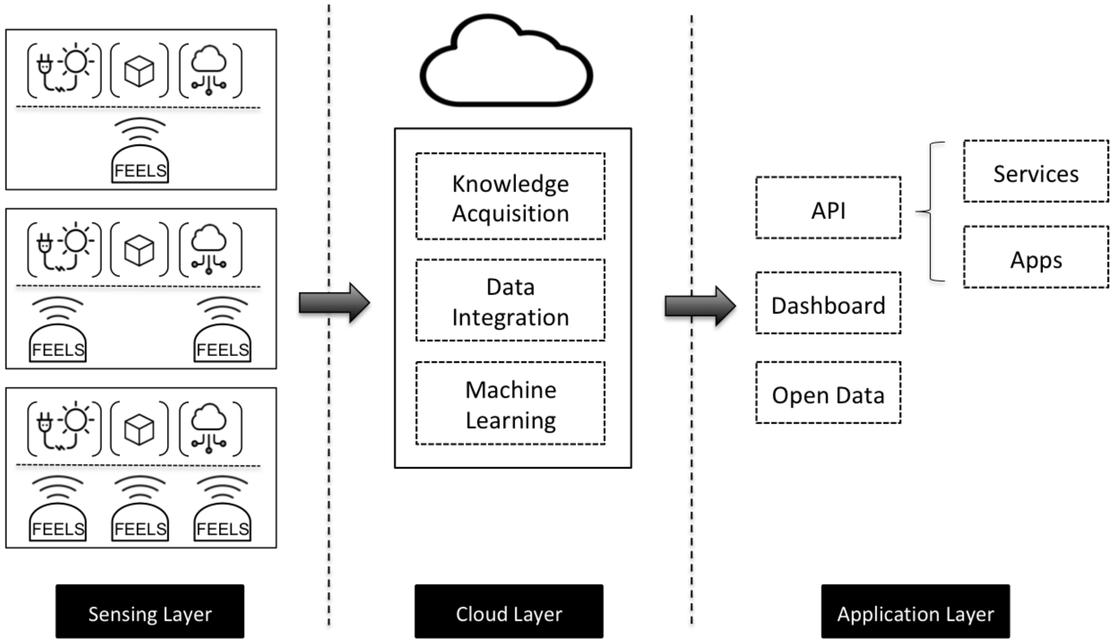


Fig. 7. Overall system architecture of City Scanner

(a) (b)

Fig. 8. City Scanner deployment on trash trucks in the City of Cambridge, MA

A. Thermal Image Processing

The main goal of deploying thermal cameras in the City Scanner project is to capture the variation in thermal flux of the built environment. In the deployment, FLIR Lepton micro thermal cameras were used to capture two thermal images per second. The FLIR Lepton camera is an uncooled infrared long-wave sensor; it can capture infrared radiation input in its nominal response wavelength band (from 8 to 14 microns) and outputs the raw thermal data. The raw data can then be converted to thermal images by applying appropriate color maps. The resolution of this thermal camera is 60x80 pixels which is a rather low resolution compared to other thermal cameras in the market. However, the resolution has been enough to show the feasibility of creating a spatiotemporal thermal map for the target built environment. The influence of sensor resolution depends on the scale of the data analysis. For instance, in case of thermal inspection of buildings, we may use a high resolution thermal camera instead. In our experiment, two thermal cameras were deployed per truck to capture thermal images of both sides of streets. The captured data were stored locally and uploaded daily to the cloud for further processing.

Various well-known algorithms were used to process and analyze the thermal images. Since trash trucks make multiple stops to load the garbage, there is a significant number of thermal images that are redundant. In order to eliminate these frames, we use the well-known Mean Square Deviation (MSD) algorithm to quantify the changes between every two successive frames. Frames with an MSD smaller than a specific threshold are deleted.

Since the target of interest in this project is the built environment, the frames that slip through the MSD frame-discarding mechanism due to human movements in the target scene should also be excluded. This is especially troublesome in situations where the vehicle is not moving and we have some human activities in the scene. To overcome this problem, we apply the MSD algorithm to the upper one-third of thermal images which is more persistent in urban areas and usually does not include human movements.

Another part of the thermal data that needs to be excluded is the open sky pixels. The sky pixels represent the average temperature of water vapor between the ground and the upper troposphere. The water vapor is warmed by absorbing part of the infrared radiation emitted by the Earth. The sky temperature is generally lower than the cloud temperature, because the water vapor in clouds absorb more infrared radiation. Since in troposphere layer, the temperature is inversely proportional to elevation, both sky and cloud temperatures are significantly lower than the ground temperature [27]. As a result, we may use this significant temperature difference to exclude the sky areas. To do so, the pixels of thermal image, which represent various temperatures in the target scene, are aggregated into a histogram of thermal flux bins. If the captured target scene includes some open sky areas, it has been empirically observed that the corresponding histogram will include a significant peak in the colder areas. Fig. 9 shows one such histogram which is generated from raw thermal data. Since our camera is non-radiometric, the thermal camera output is not the scene temperature, rather it demonstrates the incident thermal flux which is typically a value between 6000 to 9000 W/m^2. The peak on the left of the histogram corresponds to the sky area and by removing the values around the peak, we can identify and exclude the sky pixels.

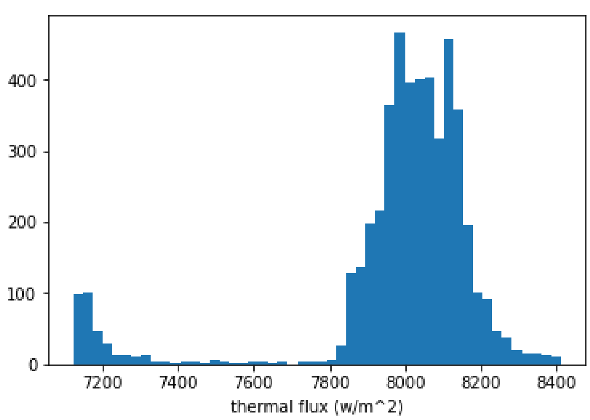
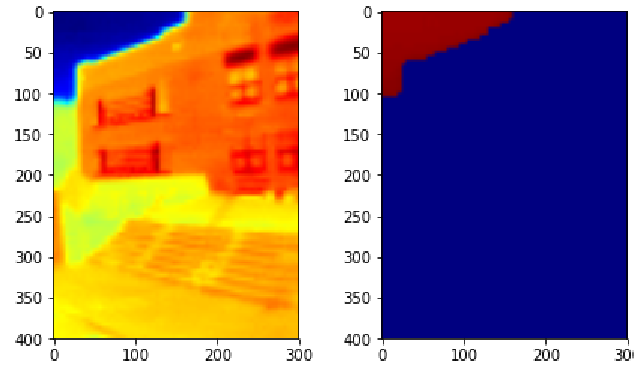


Fig. 9. Histogram of a thermal image containing the open sky area

Fig. 10 shows a sample thermal image that contains open sky areas (left) and the mask generated for this image based on the proposed method (right).

For visualization purposes, thermal data pixels were grouped into bins, which also facilitates comparisons over time. For instance, the average of pixels in the colder part of



(a) (b)

Fig. 10. Example of the empirical masking technique to exclude sky pixels (dimensions are pixels)

histogram (e.g. bins between 7600 to 7800 W/m^2 in Fig. 10 or the average of built environment part can be used to compared the thermal images over time). Fig. 11 shows the cloud of data points that are collected over course of 8 months. Each point demonstrates a single thermal images which is processed and summarized based on the proposed approach. The thermal data points form a thermal signature of target areas and one can distinguish irregular measurements and look for the reason behind these irregularities. An example of such irregularities can be seen in Fig. 11 where we have some higher temperature values on a specific day that do not follow the normal thermal pattern of the given area.

Fig. 11. Snapshot of accumulated thermal data points over 8 months

B. Air Quality Processing

Optical Particle Counters (Alphasense OPC-N2) were deployed to measure particulate matter. It did this by measuring particle counts in 16 bins ranging from 0.38 micrometers to 17.5 micrometers. This is done by illuminating one particle at a time with focused light from a laser, and measuring the intensity of light scattered. The amount of scattering from a particle is a function of the particle size which is calibrated using monodisperse particulates [32]. The normalized particle counts can be obtained by dividing the particulate counts by flow rate and sampling time. Alphasense provides a partially proprietary algorithm that makes assumptions about particle density, as well as the number of particles with diameters smaller than 0.38 micrometers to measure PM1, PM2.5 and PM10.

Note that a concern during this process is the fact that the monitor may be recording emissions from the vehicle on which it is deployed. These emissions could be different throughout the deployment, and be the most significant contributor to the noted pollution values. However, because the emissions from the trash truck are particles of sizes around 100 nm [18], and our OPC only records particles larger than 380 nm, we believe that these emissions will not have a large impact on our experiment.

Whereas there are mobile air quality monitoring projects that use high quality air monitoring sensors on Google Streetview cars [1], this deployment operates at the other end of the spectrum in terms of equipment and cost, by using low cost air quality monitors on trash trucks. By repeating the methodology that Apte et al, (2017) used, as well as using the extra information of particle counts from the OPC-N2, we can obtain a better understanding of the strengths and limitations of using mobile low cost air quality monitoring. In the following, the data analysis is detailed.

First, the road network of Cambridge will be divided into 30 meter segments (as in [1]). Measured air quality values collected over the entire duration of the monitoring will then be snapped to the nearest road segment.

The air quality data was normalized with respect to the nearest reference EPA air quality monitor in Boston. In particular, the methodology described in [1] was followed, in which each air quality measurement was multiplied by the reference value from the same hour, and subsequently divided by the daily median.

The mean and median air quality for each road segment over the duration of the monitoring experiment will then be calculated. As in Apte et al., (2017), the technique of bootstrapping will be used to gain an understanding of how reliable the mean and median values are for each segment. In this manner air quality across different road segments in the city, can be compared.

In addition, the particle count information from the OPC can be used to examine the variation of particle distribution in different parts of the city of Cambridge. Typically, coarse particles have mechanical sources, whereas finer particles are produced due to chemical transformations in the atmosphere. By understanding the variation in the particle size distribution in different parts of the city, we will be able to better identify possible sources.

Fig. 12 depicts the particulate matter interface of City Scanner visualization that allows users to browse the data in both space and time dimensions. Initial results of the previously described methodology have identified air pollutant hot spots in the areas that contain orange and red data points in Fig. 12.

C. Deployment Challenges

The main challenges encountered in the City Scanner experiments can be summarized as data transfer, power consumption, and sensing fidelity.

1) Data Transfer: Reliable channels to transfer data between the sensing node, the core component, and the cloud are essential. However, this type of routing requires higher power consumption, as a separate microcontroller is needed for each sensor. In addition, automated cloud transmission protocols can be interrupted in areas with inadequate cellular network coverage. Potential workarounds include a hard storage device or triggering batch data uploads based on certain conditions, e.g., position or time. In our deployment, we have used open WiFi hotspots to transfer data. This approach is cheaper and more stable than the use of a cellular network, but does not allow to transfer data in real-time.

2) Power Consumption: With modular sensing components, the system configuration will vary significantly based on the application; although, it is usually necessary to include an on-board power source, e.g., a lithium-ion battery, which will inevitably require servicing or replacement. In the initial experiments, one full cycle of a 60 W-hr battery permitted about 18 hours of data collection. In some cases, it may be beneficial to reduce power consumption by programming dynamic sensing properties, e.g., a reduced sampling rate when the vehicle is idle or traveling below a certain speed.

3) Sensing Fidelity: A comprehensive understanding of the context of the sensor measurements is key to properly interpreting the analytical results. The collected data are subject to systemic and stochastic noise that is introduced by the sensor, the vehicle system, or mobility patterns. For instance, the vehicle suspension system influences the acceleration data. Similarly, the instantaneous speed of the vehicle can impact air quality readings. Given these complexities, it is instructive to establish some validation procedures. Examples include, comparing some measurements with those from reference sensors, incorporating some stationary sensor data, or comparing data trends with other databases, e.g., Google Street View. In addition, it is possible mitigate the effects of sensor noise or remove erroneous values using signal processing tools.

VIII. Conclusion

Drive-by sensing facilitates the collection of dense spatiotemporal datasets of various phenomena in urban areas. The value of this paradigm is highlighted by multiple orders of time reduction, cost reduction, and increase in spatial precision compared to traditional methods for capturing urban phenomena. In this work, the urban phenomena that can be captured using drive-by sensing were detailed and the FEELS categorization was proposed to specify sensor types and organize the vast amount of potential applications. We have discussed the spatiotemporal limitations in remote and stationary sensing. With drive-by sensing, the spatiotemporal coverage is however reliant upon the mobility patterns of the hosting vehicle, divided as scheduled and unscheduled vehicles. The mobility patterns of several typical urban vehicles, such as taxis, buses, and trash trucks, were analyzed to this end. It was shown that in one day, one-third of the street segments in Manhattan, NY can be covered by equipping as few as five random taxis. On the other hand, garbage trucks and buses provided more reliable coverage in specific areas.

Fig. 12. Screenshot of the City Scanner application that allows users to explore the acquired data over space and time

Built upon advantages of related works in drive-by sensing, we have introduced the City Scanner framework. Rather than bringing dedicated vehicles to the road, we mounted sensors on existing urban fleets that practically unaltered the hosting vehicle. Since the City Scanner framework is self-contained, and consists of portable sensing components, it is less intrusive than related works. When deployed on city-owned vehicles, City Scanner gives municipal authorities the power to determine which sensors to deploy, for specific spatial and temporal coverages. Moreover, City Scanner is capable of simultaneously capturing other environmental indicators, such as thermal flux and air pollutants, which play a significant role in smart city domain by empowering advanced analytics solutions for decision makers and urban managers. These possibilities come at no other cost than the hardware. With the results of the current 8-month deployment of City Scanner, thermal abnormalities and air pollutant hot spots could be identified utilizing known methods that were customized to process drive-by data. However, as data accumulates (from multiple vehicles and over a longer time-scale) urban phenomena can be documented and understood with higher precision. We therefore envision a paradigm of modular sensing components and their corresponding cloud services for data visualization, data integration and advanced data analytics that enable cities to create elaborated applications for people in a cost-effective manner.

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