

AMSense: How Mobile Sensing Platforms Capture Pedestrian/Cyclist Spatiotemporal Properties in Cities

Alphonse Vial, Winnie Daamen, Aaron Yi Ding, Bart van Arem, and Serge Hoogendoorn

Abstract—We present a design for a novel mobile sensing system (AMSense) that uses vehicles as mobile sensing nodes in a network to capture spatiotemporal properties of pedestrians and cyclists (active modes) in urban environments. In this dynamic, multi-sensor approach, real-time data, algorithms, and models are fused to estimate presence, positions and movements of active modes with information generated by a fleet of mobile sensing platforms. AMSense offers a number of advantages over the traditional methods using stationary sensor systems or more recently crowd-sourced data from mobile and wearable devices, as it represents a scalable system that provides answers to spatiotemporal resolution, intrusiveness, and dynamic network conditions. In this paper, we motivate the need and show the potential of such a sensing paradigm, which supports a host of new research and application development, and illustrate this with a practical urban sensing example. We propose a first design, elaborate on a variety of requirements along with functional challenges, and outline the research to be performed with the generated data.

I. INTRODUCTION

While urbanisation is competing claims on space in cities, it is essential to understand peoples' movements for the design and management of infrastructure, safety, mobility, as well as for public and private transportation. The new digital layer emerging in cities that includes sensors and pervasive mobile systems can help observe and manage different walking and cycling mobility and movement patterns by gathering large amounts of spatiotemporal data. Data about pedestrians and cyclists — so-called active modes — dynamics in urban environments are essential for different types of spatiotemporal analyses, models and behavioural theories. Nowadays for instance, stationary sensing systems are used to continuously monitor pedestrians and cyclists at fixed locations over time (e.g. camera-systems at intersections). Observations about active modes, however, could also be collected with spatially distributed sensing platforms and shared among each other. Although a dense network of stationary observers could possibly meet the desired objective (i.e. providing spatiotemporal mobility information), such large network deployment may require an excessive number of sensor nodes in order to achieve satisfactory sensing performance, at high infrastructural costs. In addition, a static network is not flexible and would not adapt to unpredictable network dynamics or changes of the physical environment. For instance, events due to sensor failure, coverage holes, and changes in the infrastructure or mobility behaviours that are likely to happen in an urban context.

In the past, a number of studies have used vehicles to monitor the urban environment (e.g. traffic, pollution, road conditions). As the number of sensors in a vehicle has increased by the thrive to so-called intelligent vehicles it evolved from a purely mechanical to a genuine cyber-physical system that continuously streams diverse data in real time. Some of these data are essential to the proper working of a vehicle's components and functionalities, but at the same time the captured surplus of data could be used for other purposes [29]. The ever increasing number of sensors in intelligent vehicles (e.g. LIDAR, RADAR and vision) enable a wide range of urban monitoring applications, thanks to their ample sensing, storage, processing, and communication (e.g. V2V, V2I) capabilities that have not been utilised for this purpose up till now. In the context of this research, an intelligent vehicle can be understood as mobile sensing platform, capturing pedestrian and cyclist spatiotemporal properties from the number of distinct signals it generates. In a foreseeable future, large groups of connected intelligent vehicles, are expected to be deployed in cities and potentially coordinate their actions through communication networks. The promising nature of these connected mobile sensing platforms enables to carry out tasks, proven to be difficult when performed by a single vehicle, or static sensor.

In this paper, complementing current active mode sensing methods, we propose a novel sensing system, called AMSense, that grounds on connected intelligent vehicles as mobile sensing nodes in a network, to capture pedestrians/cyclists spatiotemporal properties in cities. In this dynamic, multi-sensor approach, real-time data, algorithms, and models are fused to estimate spatiotemporal densities, velocities and flows of active modes using presence, position, and movement data collected by a fleet of mobile sensing platforms. Active mode data shall be extracted, processed, and shared through a mobile sensing network.

Contributions. AMSense represents the first pedestrians/cyclists mobile sensing system that innovates in such a fundamental part of active mode research, especially in the provision of real-world, and real-time data. Mobile sensing platforms that collectively gather active mode information in a network, is a rich application domain with many challenges left to be resolved. We therefore characterise design constraints and requirements, in terms of sensing performance, processing, and control, of such a novel active mode sensing system. Probably the most important contributions of this work revolve around the combination of data, the extensive temporal

and spatial scale, and the dynamics of the data collection system. This novel sensing paradigm offers a number of advantages over more traditional methods using stationary sensor systems or more recently available data from mobile or wearable devices, as it reduces effort and cost to collect pedestrian/cyclist data, at an extensive temporal and spatial scale, while providing answers to intrusiveness and scaling effects. This paper presents a theoretical design of such a sensing system.

The remainder of the paper is organised as follows: Section II covers different types of active mode research as well as their required data, and compares current data collection methods. Section III illustrates the proposed work with an urban sensing example, and addresses main requirements to such a novel sensing system. Section IV delivers insight into architecture and functions of our proposed mobile sensing network, while section V elaborates on how to derive active mode spatiotemporal properties in large urban environments. Section VI concludes this paper and highlights future research directions.

II. PROBLEM FORMULATION

The use of data is not only crucial for the empirical observation of active mode movement behaviour, but at the same time, data is decisive for the development of models, their calibration and validation. Yet, datasets providing comprehensive pedestrian and cyclist mobility information on road-, lane-, or subject-level, are remarkably rare given the rise of sensors in cities. The need for high-quality datasets that capture pedestrians/cyclists in large urban environments is undisputed. This section primarily aims to clarify that different tracks of active mode research require different types of data. Note that we hereby only focus on pedestrian/cyclist movement data collected in urban environments. This section eventually gives an overview of current real-world data-collection methods.

A. Different data for different active mode research

Pedestrian and cyclist dynamics in cities can be described and predicted at three behavioural levels: strategic, tactical and operational [18], [12]. Several modelling approaches at three behavioural levels have been proposed in the past, both micro- and macroscopically. A comprehensive overview of the main modelling approaches is described in [13] for pedestrian models, and [38] for cyclist models.

Various approaches that study active mode flows and behaviours require pedestrian/cyclist traffic-related data, providing information about movements in space and time. Different models and behavioural theories require different data; mainly varying in spatial scale, accuracy, and granularity. In this context, data granularity represents the scale, or the level of detail of a dataset, while data accuracy relies on technical capabilities of the data collection system. Furthermore, the temporal character of the data use, or in other words its value loss over time, is related to the aspect of real-time. In essence, studies at strategic and tactical level usually use movement data that was aggregated up to a certain extent, and thus conceivably requires data at lower granularity and accuracy. At the operational level,

microscopic models however require particularly detailed (i.e. high granularity and accuracy) movement data along observed individual trajectories, as they examine, for instance, variations in speed, directions, relative positions, or headways. Densities, speeds and flows can however also be observed as fundamental macroscopic relationships, at higher levels of aggregation.

Pedestrian and cyclist data can thus be used in a variety of forms and types, each satisfying a distinct track of active mode research. Data-driven studies vary in spatial scale, either over the entire network, a link, or a cross-section, and require more or less time-sensitive information.

B. Active mode data collection methods

Real-world datasets are required for any empirical model of active mode behaviour and analyses of movement patterns. Humans are considered to be dynamic by nature as they move at varying speeds, have different body postures, and wear a range of widely varying clothing that may mask their body shape. These static and dynamic traits can be captured by different types of sensors when an active mode is present (e.g. shape), or performing an activity (e.g. walking/cycling).

Researchers studying active mode urban mobility have largely used data gathered with stationary sampling technologies. Image based sensors (e.g. camera) and infrared or laser sensors are most frequently used for microscopic and macroscopic measurements at local scale (e.g. cross-sections) [19], [37]. Pedestrian trajectories, for example, are usually collected exploiting camera footage [19]. Also active sensors such as RADAR and LIDAR are used accordingly to a specific application or task. While these sensors gather data at different accuracies, they are able to provide data at a high level of detail, mainly used for local level walking and cycling behaviour, or more aggregated for studying traffic flow. Major difficulties however revolve around precise tracking of observed pedestrians/cyclists, recognition of the same person between two sensors, and challenges related to occlusion that limits the continuous sensing of an active mode in space and time. The overall cost of such stationary sensor data is not incontestable as the installation, service and maintenance cost of infrastructure sensors (e.g. camera installation as traffic detector) is expensive and inefficient for information provision at larger spatial scale (e.g. network). It is because of the considerable investment in infrastructure and setup, that stationary sensor data likely has a low level of spatial resolution (i.e. located at main intersections, or roads).

Micro- and macroscopic measurements at greater spatial level, however, have become more and more utilised thanks to technological advances linked with mobile technologies. Yet, the emergence of ubiquitous mobile positioning and tracking devices have enabled the gathering of large amounts of data, in a technically convenient and economically cheap way. The movement of pedestrians/cyclists within a given area can be observed from the digital traces generated by a variety of sensing sources, and requires lower accuracy. For instance, frequently used positioning systems (e.g. GPS), are suited to study mobility patterns and route/activity choice, while the variations in their accuracy, where errors can be caused by

satellite orbit or receiver issues, make them inappropriate for microscopic movement behaviour analyses. This technological integration hence offers an opportunity to analyse mobility patterns, across transportation modes, and potentially in real-time. Over the last decade, digital footprints of human mobility patterns have enabled urban planners, computer scientists, sociologists and engineers to better understand dynamics in cities. Past studies have mostly used GPS location updates [35], [42], mobile phone records (i.e. CDR and sightings data) [3], [16], Bluetooth [39], Wi-Fi [9], and social media data [5], [21]. Still, these data require direct or indirect collaboration of the tracked target, and thus has to deal with drawbacks in terms of representativity of the sample. But it is the intrusive nature of these participatory mobile sensing methods, relying on smartphones, wearables and other logging devices, which represent a major disadvantage and potential limitation as for data sparseness in some areas. In addition, while call records data (mining of mobile phone data) has proven to be valuable in vehicular traffic, it presents, however, high disadvantages due to spatial resolution limitations, as well as accessibility of the dataset itself. The spatial resolution may represent a bigger issue for pedestrian, than for cyclist mobility, as cyclists travel further, and hence more coarse data better describes their behaviour. Thereby, deriving mode choices remains more difficult than inferring route choices [4].

Bluetooth and Wi-Fi are currently referred to as the most suitable technology to measure active mode traffic in a broad set of traffic conditions: from low traffic volumes to high volume flows in an urban network. They allow tracking of individuals through a network, one of their main advantage being the low cost of measurements [8]. Wi-Fi, however, appears to be more generic and thus more suitable. At the same time, owing to the pervasive coverage, low latency and high bandwidth, the fifth generation (5G) of mobile networks are becoming another promising solution for urban scale mobility measurement [10], [40].

Overall, employed data collection methods are restricted to distinct areas of active mode research as each only gather certain types of data. Yet, there is no data collection method known that provides information about pedestrian and cyclist spatiotemporal properties on at different accuracy, as well as various spatial and temporal granularity, in urban settings. The need for advanced tools, and scalable systems that provide answers to spatiotemporal resolution, intrusiveness, and dynamic network conditions emerges.

III. FUNDAMENTALS

The operational objective that we address with this work is to enable researchers and policy makers to “observe active mode movements in cities at all time“. Fig.1 exposes the proposed active mode sensing system, AMSense, to an urban traffic setting that represents pedestrians walking on side-/crosswalk, and cyclists cycling on a designated bike path/road. In a real-world situation, however, many other traffic situations can be encountered due to the complexity of urban dynamics that continuously provoke unpredicted events. Pedestrians are usually being described with a normally distributed walking

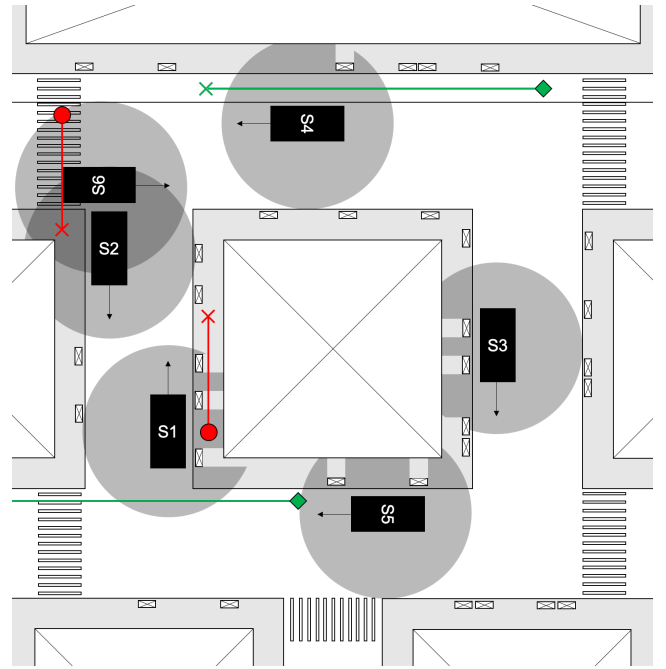


Fig. 1. Urban sensing scenario in which mobile sensing platforms (black rectangles) capture pedestrians (red circles) and cyclists (green diamonds), and provide information about their presence, positions, and movements. Data about an active mode is only generated if present in the sensing radius (grey circles) of at least one vehicle.

speed, whereas cyclists exhibit a greater range of speeds but more constant, and thus are being described with a wider distribution and greater mean velocity. In reality, this flexibility of speeds and directions can lead individuals to fully stop their motion, carry out less predictable movements (e.g. sidestepping), or disobey traffic rules (e.g. crossing at an unsignalised intersection). In addition, large intersections, multilane roads, and shared spaces are continuously altering the sensing system’s requirements as its mobile sensing platforms dynamically sense the environment while being in motion. Overall, following urban mobility patterns, higher densities of individuals lead to a higher sensing demand while higher densities of mobile sensing platforms lead to a higher sensing supply.

A. Illustrative example

To extend the technological and spatiotemporal flexibility of today’s data collection systems, we consider the following: every vehicle in a city has one or more attached sensors, and acts as a mobile sensing platform. These sensors are capable (individually or in combination) to capture pedestrians/cyclists’ mobility properties in time and space. The generated information of a vehicle’s perceived environment is filtered, and relevant data diffuses across a network of mobile sensing platforms. The information collected from each of the sensor-equipped vehicles is fused, increasing the amount of available data at a certain location, and eventually providing much greater local detailed knowledge of a city’s neighbourhood, road segment, or sidewalk, and potentially in real-time. In Fig. 1, AMSense is exposed to an urban sensing

situation in which pedestrians and cyclists are observed by one or more mobile sensing platforms. The sensor equipped vehicles drive along the road network and continuously collect sensor data of their surrounding environment. This sensed data can then be processed to seek for the information of interest that is presence, locations, and movements of observed pedestrians and cyclists. These data can be shared among vehicles and communicated to a remote monitoring and control unit for additional processing, visualisation, and analyses. A comprehensive perception, in such a dynamic environment, requires the interplay of different mobile sensing platforms to obtain a detailed representation of the scene, and accurate data about sensed targets.

Collecting active mode spatiotemporal information in such a way could increase flexibility in space and time, and data could be generated at different levels of granularity and accuracy. Ideally, this sensing paradigm enables to perform different types of studies ranging from the operational level applying very detailed local data along individual pedestrians/cyclists' trajectories, over using data potentially collected with lower accuracy and aggregated to a lower degree of representation that would be applied to study macroscopic phenomena, up to studies at the strategic/tactical level using even more aggregated data over the entire network.

B. Requirements and performance metrics

A major trait of AMSense, is that it has to operate in increasingly unstructured environments, which are inherently uncertain and dynamic. We believe there are significant robustness and scalability advantages when using vehicles as a mobile sensing platform that collectively achieve a global objective, while being less intrusive, and less limited by practical constraints (e.g. power consumption), network reliability, and local processing capacity, than any data collection method presented earlier. For instance, vehicles are typically not affected by strict memory, processing, storage, and energy limitations, which enables the integration of various sensors, wireless transmitters and processing components. In recent years, several advanced technologies such as lightweight virtualization and edge computing have been applied to smart vehicles to enable novel applications and dynamic service deployment [25], [31], [32].

We identify four prevailing elements that can generate different types of active mode data by using a network of mobile sensing platforms: network, sensing, processing, and communication. These fundamental requirements that make AMSense scalable to spatially large urban environments, and adequate for real-time implementation on rapidly moving vehicles, are illustrated as follows.

Note that the idea of a system that continuously collects data on pedestrians and cyclists requires ethical, privacy, and security considerations, which shall be covered in future research. Therefore, this paper only draws the attention to such issues and advocates the need for an optional on-demand privacy component, consisting of tailored algorithms and a series of mechanisms for implementing potential privacy policies in each of the elements outlined below.

1) *Network*: Sensor networks are typically deployed in static environments, with application specific tasks. A highly dense all-static sensor network may possibly meet the Quality of Service (QoS) (i.e. service of providing spatiotemporal mobility information) requirements in an urban setting akin to Fig. 1. However, studies have shown that sensing and networking performance of wireless sensing networks can be improved by integrating sensor mobility [27], [36]. This for instance, is coupled with advantages for node deployment, and configuration strategies, supporting coverage and control in vast areas. These are required since our sensing paradigm relies upon a minimum coverage percentage (i.e. percentage of area sensed by at least one vehicle). The control of a flexible temporal and spatial resolution schemes can be translated into coverage robustness as to maximise the number of vehicles sensing the same location. Furthermore, as massive data is generated by diverse sensors from each mobile sensing platform in the network, at vehicular speed, it is required to minimise the congestion probability (i.e. traffic load must not surpass the bottleneck capacity of the links) when data is shared along the network. In addition, the network is required to be robust and energy efficient in routing. Meanwhile, potential applications may require data to be processed real-time, thus minimal response times (i.e. latency) are required within the network. At the same time, data needs to be fresh, that is the most current status for every measurable feature, requiring low network latency from the time of sensing to the time of processing.

2) *Sensing*: Sensing components serve as fundamental as they generate the raw data which is used later to detect, and further interpret active modes spatiotemporal properties. Different types of active mode data are required to be collected by the sensors, integrated on the mobile sensing platforms. Although different data can be gathered by diverse sensors that generate data at a variety of sampling rates and accuracy, a minimal measurement accuracy is required. Thereby, the data quality is expressed by means of data accuracy and data granularity. The latter refers to temporal and spatial resolution of the data. Robustness needs to be maintained to avoid single sensor deaths (i.e. sensing robustness), and expands a vehicle's sensing capabilities (e.g. field of view). In order to generate the data, sensing elements require a minimum sensing range and power. Note that both sensing range and power have a major influence on the coverage requirements introduced earlier. The sensing application must therefore include energy-aware adaptation to dynamically adjusted sampling rates as each sensor type generates data at a different rate based on the targets or environment.

3) *Processing*: On top of sensing, mobile sensing platforms also require embedded computational resources for data processing. A processing element is key, and can be integrated in many ways. While the processing can be performed at a centralized server in order to have a lower impact on resources, some basic filtering and anonymization of the data can also be performed before actually sending it. Especially given a proliferating amount of data will be generated, processed and stored, edge is becoming part of the processing layer besides the on-board car processing and remote cloud processing [31].

By using edge, a significant amount of processing can be offloaded before sending information to control units. Since it is infeasible to transfer the full amount of raw sensor data at all time, on-board processing and edge processing are required up to a certain extent before further transmission. To effectively perceive the dynamic movements of active modes, the sensing system requires to continuously feed real-time sensor data into the processing module (i.e. frame-rate), and further understand the captured scenes (i.e. processing latency) by extraction of only relevant information. Moreover, real-time processing speeds are required, as well as pre-processing procedures to reduce noise of analysed signals dynamically depending on the application. A successful implementation of such a system requires state-of-the-art algorithms.

4) *Communication*: Data providing information on pedestrians/cyclists is required to be shareable around the network, in order to eventually be available for further analyses. Vehicular traffic is network-restricted, mainly following traffic patterns (i.e. commuting hours), and travelling at maximum 60km/h in inner city-rings. Vehicles require communication capabilities that allow them to send and receive information packets to other mobile nodes, and potentially to additional control units. Some systems use short-range communication not just for detection but also for enabling collaboration between sensing platforms. As this sensing network shares time-sensitive information, data needs to be fresh (novel) and transferred in near real-time. The freshness of that data can vary, depending on how frequently a sensor is relaying readings, and is defined by sensing the correspondent application. A reliable communication is therefore required, providing answers to both potential bandwidth and latency issues. In a reliable network, the mobile sensing platforms need to transmit updates constantly, providing most current status for every sensed feature [22]. The aim is therefore to maximise the novelty of the data received at any moment, while at the same time avoiding data congestion.

IV. DESIGN OF AN ACTIVE MODE SENSING NETWORK

Advances in sensing, computing and communication have driven efforts to study sensor networks, composed of a large number of densely deployed sensor nodes with self-organization, cooperative effort and on-board processing capabilities [1]. The vehicular based sensing paradigm we propose in this paper, is in-line with the Vehicular Sensor Networks (VSNs) for various urban monitoring tasks [2], [20], [26], [30]. In this section, we propose the design for AMSense that captures pedestrian and cyclist spatiotemporal properties in urban areas, where a high concentration of vehicles equipped with on-board sensors can be expected, and thereby introduce the network model and its functional architecture.

A. Sensor network characteristics

The requirements described in the previous section lead to the definition of major characteristics displayed in Table I, and comprehensively described in [6], for such a mobile sensing network to be designed.

In a traditional multi-sensor system, large scale networks take in different *dynamics*: with mobile, stationary or aerial sensor nodes. We identify two distinct features for a sensing network that observes pedestrians/cyclists using vehicles as sensing platforms: i) vehicles are highly mobile, moving at different speeds along the urban street network, and ii) their mobility patterns are, to some extent, predictable due to the constraints imposed by roads, speed limits, and commuting habits (patterns). While both are typical traits of a vehicular ad-hoc network, their mobility extends the spatial and temporal scale of sensing and networking performance. Data about pedestrians and cyclists can thus be collected at many different locations within the network along the sensing platforms' trajectories, and responding to dynamic changes induced from the urban environment.

Due to mobility, the *quantity* of sensors in a network can thereby vary by several orders of magnitude over a day. As we utilize vehicles as mobile sensing platforms, and mobility patterns are strongly affected by the global mobility demand and the topology of the street network, the number of vehicles in cities follow a negative binomial distribution [7]. The performance of sensing is eventually directly influenced by this characteristic, as the accuracy of estimated traffic flow variables increases with the number of operating sensing platforms observing that same scene. In addition, the spatial dimension becomes feasible, as sensing of multiple areas can occur in parallel.

Another closely tied network characteristic, with direct impact on the QoS of AMSense, is the *deployment* of sensing nodes. The sooner a pedestrian/cyclist is detected the better for the global network information quality. The optimal placement of sensors is therefore essential to meet requirements for entirely observing an area or a target. We chose to use urban vehicles (e.g. private, fleet), enabling wide coverage at reduced cost, as mobile sensing nodes to create mobile ad-hoc networks and form an inter-vehicle communication network.

Coverage builds upon the quantity and deployment strategy of sensors present in a network. While sensing coverage can be sparse or dense in urban settings, due to varying traffic densities, we assume nodes to be deployed with uniform density, q , subject to some temporal traffic and local patterns. The capabilities of deployed sensors in dense network vary when used individually versus when employed collectively. The coverage ratio (e.g. partial, full), with a density q that guarantees redundant coverage of an area to be monitored, depends on the sensing application and the type of data needed. For instance, besides communications and processing capabilities, network-wide microscopic sensing task (e.g. trajectories of pedestrians/cyclists in a network) can benefit from a high quantity of sensing platforms and large coverage ratio, as detailed representation of pedestrian or cyclist movements. In contrast, local macroscopic sensing (e.g. densities of pedestrians/cyclists on a road segment), requires less information, thus a limited coverage is sufficient to provide acceptable traffic estimates. Already a small number of fleet vehicles could satisfy the coverage requirements [33] for some specific active mode sensing tasks at macroscopic scale. We note that as traffic patterns contain distinct statistical properties,

TABLE I
OVERVIEW OF DESIGNATED MAIN CHARACTERISTICS FOR A SENSING NETWORK THAT USES VEHICLES AS MOBILE NODES.

network characteristics	type	key performance metrics
dynamics	mobile	spatial resolution
quantity	mobility demand	temporal resolution
deployment	private vehicles, fleets	deployment strategies
coverage	spatio-temporal traffic pattern	redundant coverage, optimal allocation
composition	heterogeneous	sensor fusion
communication	wireless	low latency, high bandwidth, 5G
power source	internal, on-board	energy consumption
architecture	multi-layer hybrid, decentralized	scalability, real-time implementation, privacy

network-wide traffic state may be inferred from a learned statistical model.

The *composition* of a sensor network can be homogeneous or heterogeneous. As illustrated in the scenario of Figure 1, the composition of AMSense is heterogeneous as to accommodate the interplay of different sensor types.

In addition, sensor nodes need to cooperate by means of *communication* to maintain consistent real-time local information, which consists of sending and receiving data via a communication medium. This enables the sensing vehicle to exchange information with other vehicles in the mobile network. The AMSense communication medium is over wireless (e.g. 5G and WiFi) to meet the low latency requirement.

The *power source* represents an influential limitation as various sensors, connectivity components, and computing equipment surely have important energy demands. For vehicle networks, a higher consumption of energy could eventually translate into reduced vehicle range. As this work presents the potential of future intelligent vehicles' "data exhaust", we will not consider issues related to continuous power delivery capabilities for the early applications.

Three different types of processing *architectures* are typically defining a mobile sensing network; centralized, distributed, or hybrid. Raw collected data needs to undergo communication and computation, in order to be further processed and aggregated to provide information about pedestrian/cyclist presence, positions, or movements. While in centralized architectures, all captured sensing data is instantly transferred to a central processing unit, this approach suffers from potential computational bottlenecks because of the sheer size of generated data, and is prone to crash in case of central unit failure or death. The inherent spatially distributed nature of multi-vehicle networks, which rely on a distributed communication and computation architecture, however, invalidate classic centric approaches. Hybrid processing architectures, in contrast, use a distributed approach to perform some level of local computation at each node, yet, still rely on a central unit to perform overall data fusion. We propose a multi-layered hybrid architecture that grounds on distributed and decentralized communication and computation, in which vehicle nodes communicate locally with surrounding vehicles. This allows the communication overhead to scale well with increase in network size and efficiently use parallel processing to process real-time data. This allows complete parallelisation of any algorithm, speed increase and proves to be a very survivable system.

B. Functional architecture

Fig. 2 displays a multi-layer mobile sensing architecture with its primary functions. Remind that we make use of vehicles' sensing capabilities without interfering with their native operation. AMSense can be divided into multiple layers based on information hierarchy and computing capabilities. In a top down order, a cloud layer, on top of which diverse applications can be developed, governs an edge data processing layer that connects physical devices (i.e. mobile sensing platforms) with the cloud. Units and modules follow distinct objectives, and are represented in the figure to provide functional context.

Cloud Layer. At a governing level, the cloud layer (Online Fleet Operation (OFO)) offers resources for monitoring and managing the mobile sensing network, along with resources for further complex data analyses and long-term storage, while streaming information from mobile sensing platforms at any given time. This dynamic layer, manages the network, and processes less time-sensitive, non-raw data, which is already preprocessed through filtering and aggregation mechanisms by underlying layers. Information reaching the OFO can either be used for sensing operations management (e.g. data acquisition) or data processing tasks. In the first place, this layer enables interactions between many possible applications, including their collaboration and data exchange, potentially in real-time. Applications are developed on top of the cloud services and provide users the possibility to further analyse the collected datasets through APIs. Those make the data available for running additional data analytics, machine learning, and visualisations on cloud servers that provide deeper insights in the collected data. In addition, the OFO offers various other services, such as coordinating user-defined sensing tasks. As such, sensing can either be performed continuously in the background or triggered by a request via cloud-based applications. Requests (i.e. sensing tasks) can be defined specifically, including information about possible targets, planned routes and sensing behaviours, after which, the OFO sends task-related information to respective sensing platforms. The data collection and coordination process of those sensing tasks is performed autonomously by the cloud and underlying edge layers, based on value specific context selection that is to choose the best data sources for defined sensing tasks, without the need to contact the cloud service. A mobile sensing platform can thus wait for incoming tasks, start the data collection, and return results, or may simply publish pre-processed data without a specific request, whenever a connection is available.

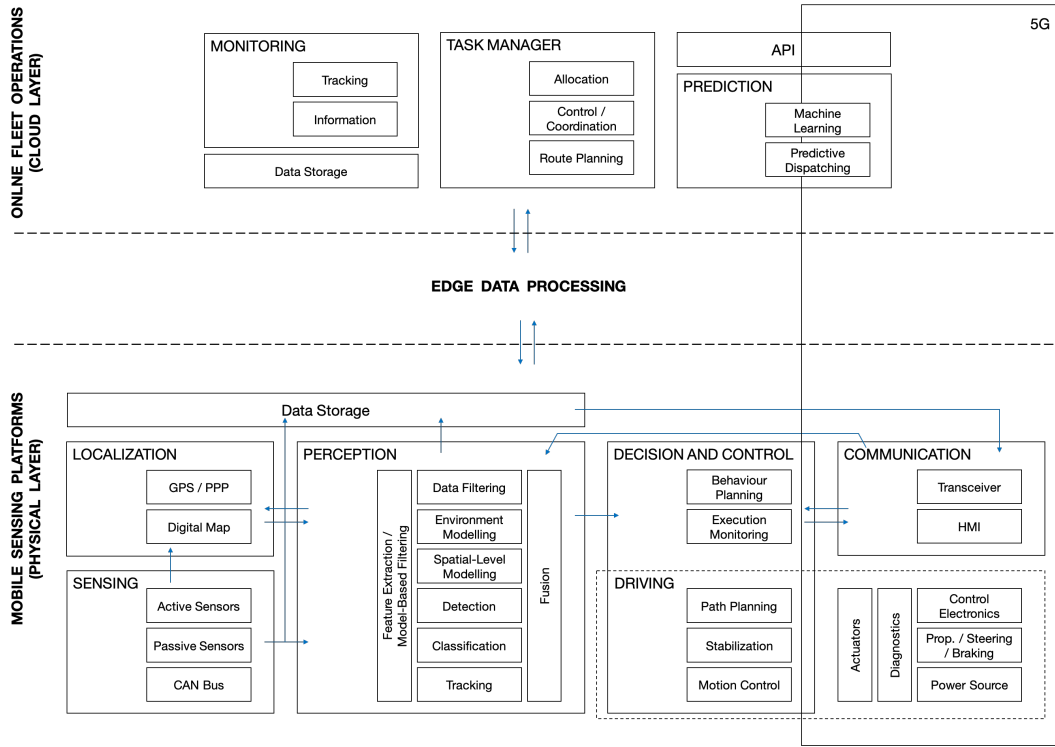


Fig. 2. A high level, multi-layer architecture of the proposed mobile sensing system AMSense, in which blue arrows represent data flow between different units.

While the freshness of data plays a major role, data can be stored locally at the edge (e.g. on-board) or globally (e.g. cloud server), before or after pre-processing, and can be retrieved for further analyses.

Edge Data Processing Layer. Because of computational and QoS requirements and the sheer size of collected data, we move and offload computation in the proximity of mobile devices by introducing an intermediate layer responsible for additional data filtering, aggregation, processing and storage. This edge data processing layer entails the computing paradigm that delivers similar service as cloud computing, but by different means to enable a range of new benefits such as low latency, context awareness and mobility support. In addition, edge processing layer delivers similar utility computing model as cloud computing (e.g., SaaS, IaaS, PaaS) but in a decentralized manner, where computing power is brought to the network's edge infrastructure. Therefore, the processing tasks on the gathered data happens at the edge, that is on mobile sensing platforms and the edge infrastructure between mobile devices and cloud services. This design reduces the load of data on the network and the cloud, as sensing, processing, aggregation and application execution are distributed over the entire network, and potentially in real-time. In contrary to a plain middle layer solution, our edge layer includes programmability and flexibility via software-defined networking (SDN) [24] and network function virtualization (NFV) [17] to deliver ubiquitous processing capabilities across a wide range of heterogeneous hardware. For instance, the AMSense edge layer will provide image processing and raw sensing data pre-processing simultaneously. Given the heterogeneous

characteristics of various instances deployed in AMSense, the edge data processing layer cooperates mutually with both cloud layer and physical layer, by acting as a bridge between elements that require dedicated interaction.

Physical Layer. Apart from native components and functions that are necessary for a vehicle's driving, core components of a sensing platform include sensing, localisation, processing (i.e. perception, decision control) and communication.

The *sensing module* is based of sensors covering a vehicle's external sensing capabilities, as well as internal sensors that provide information about a vehicle's internal state. The sensing module itself remains configurable, as any vehicle integrated sensor may be activated, and thus send data, on the grounds of the different types of application. Sensor data can directly be used for localisation and map provisioning, and thus holds a common interface with the localisation module.

Although sensing and localisation are strongly linked and together form the core source of data, the latter is an independent module that has to provide two types of information on higher abstraction level. First, mobile sensing platforms are required to localise themselves (ego-localization) on a street network. The *localisation module* therefore requires to perform mapping, map updating and provides map information to other modules. Second, mobile sensing platforms are required to localise detected pedestrians and cyclists. Sensors thereby provide data input to obtain an absolute, global pose from localisation algorithms. Satellite technologies, as traditional GPS, are largely sufficient on a macroscopic level for road localisation. But shrinking down the scale to the order of a few centimetres, to perform localisation on lane- or subject-level

in dynamic urban environments, localisation exceeding GPS accuracy is required. While some techniques to improve the accuracy of a traditional GPS system exists [23], the required stringent level of accuracy and availability for such mobile sensing application can be achieved using additional sensing sources (i.e. LIDAR and camera) to produce a more accurate, robust and reliable localisation. The accuracy of an active mode's position thus depends on the technical characteristics of the sensing vehicles that capture this individual, but can also be increased with additional positional measurements that capture the individual, fused from different locations and perspectives.

The sensing module transfers raw sensor data via an interface to the *perception module*, with additional information originating from the localisation module that follows. Different types of sensors such as LIDAR, RADAR, long-range ultrasonic and forward-facing or surrounding-view camera sensors, provide depth information of a vehicle's surroundings. This data aggregate, for instance, can later be used for purposes of environment modelling. Note that sensors of each mobile sensing platform need to be considered independently, as they are subject to a vehicle's ego-motion. Vehicles have different perspectives on a scene, depending on their location and the orientation of their sensors. For these reasons, data filtering is performed to integrate one vehicle's captured scene (e.g. point cloud), to another vehicle's local view, observing that same scene, at the exact same time. With detailed information about a vehicle's orientation and position, a transformation can be performed that brings the data into a universal-VSP bound coordinate system by estimating the ego motion. In other words, dynamic (e.g. pedestrians) and static (e.g. infrastructure) elements from a scene that are output of the mentioned sensors, can be associated to three dimensional position information, using pre-computed 3D maps of the environment. Furthermore, several algorithms (e.g. feature extraction, model-based filtering) are executed to perform active mode detection, and self-monitoring of surrounding vehicles. Algorithms such as for pedestrian/cyclist detection and classification, or tracking, ground on deep neural networks. While they require substantial computing resources, their accuracy and speed is proportional to the computing resources available to them.

The *perception module* has interfaces to sensing, localisation, planning and control, as well as to the communication module. Perception data can directly, or indirectly, be used for broadcasting information via the communication interface to other vehicles, as to extend surrounding vehicles field of view that may be limited (e.g. visibility) [34]. This perceived information is transferred to the decision and control module, where the real time map of sensed active modes and their environment is updated. Note that while the processing module is fixed, the *storage module* can be customised depending on application and usage.

The *communication module* embeds the 5G connectivity and spans across three layers, as illustrated in Figure 1. From architectural perspective, this implies that the communication module integrates the cloud computing, edge computing, SDN, NFV, and combines various wireless elements to deal with the

requirements of AMSense services. As 5G connectivity in the future will be regarded as one of the mandatory common-pool resources (CPR) similar to water and electricity, the communication module also cater to the requirements from governmental and economical angles. This will establish a strong connection on the regulation and management in terms of interoperability, safety, cost of maintenance, public-private ownership, wireless spectrum bidding and allocation, which is necessary part of AMSense.

The *decision and control module* has interfaces to the perception and communication modules, as well as towards the actuators within the native *driving module*. Algorithms in the decision and control module are the primary users of the processed information. While path planning, stabilisation and motion control are performed during the native driving of the vehicle, and thus do not relate to the monitoring system, behaviour planning and execution monitoring, however, use information from perception module to potentially perform detection or tracking tasks. Those are based on messages originating from OFO interface. As mentioned before, depending on the application, sensed and perceived data can be provided at different temporal and spatial levels for active mode movement mapping updates. Behaviour planning entails operating for active mode detection or tracking where waypoints are targeted between which a route needs to be planned. Behaviour planning does however not only select the modelled movements, but also plans how it has to be executed. This manoeuvre information (e.g. orientation, velocity) may be utilised by succeeding vehicles, and provided with lateral and longitudinal trajectory data to best capture the targeted active mode. For instance, the knowledge of a no-detection field (e.g. occlusion), is valuable and may affect the path planning of following vehicles by changing to a lane with better view to capture a pedestrian on the sidewalk. In addition we also include execution monitoring to this module. This ensures that assigned tasks are executed as planned, and possible deviations lead to adjustments in the sensing operations. In the future, it could allow sensing vehicles to actively reposition themselves in order to optimise their sensing orientation (i.e. distance, angle), using path planning that finds an optimal path when a task is assigned, while recalculating positional deviations.

V. ACTIVE MODE SENSING APPLICATIONS WITH URBAN VEHICLES

The complexities and edge-cases of scene perception, as well as the limitations and imperfections of sensors, make capturing the presence of active modes from a moving sensor platform full of open challenges. Using data from a single sensor source, is not necessarily sufficient to differentiate individuals from other objects in urban environments. We first categorise different sensing technologies before diving into sensor applications and examining scenario related parameters.

A. Sensor configuration

To start with, we classify the different sensors into those capturing the internal states of the vehicle and those capturing the states of the environment in which the vehicle operates.

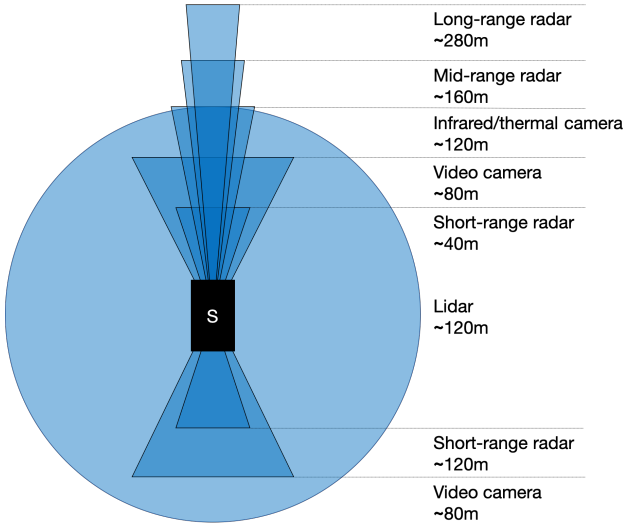


Fig. 3. Illustration of a possible sensor configuration on a mobile sensing platform.

The prior are described by the vehicle CAN bus, a serial broadcast bus that allow near-real-time management of most sensors and electronic devices embedded in the car. These highly integrated sensors measure steering angle, brake pressure, or acceleration rate are input for actuators related to a vehicle’s native driving task. Such data may however be used to indirectly detect interactions with active modes, and hence denote their presence. In the context of driving behaviour analysis [15], [28], the identification of changes in a driver’s behaviour could not only help recognizing hazardous situations but may also lead to describing active mode presence in real-time. For instance, think of a vehicle firmly braking in front of a pedestrian crossing (e.g. zebra). The braking operation can directly be read from outgoing sensor signals via the CAN bus, while the zebra crossing may be identified based on combination of position and 3D-map. Fusing the data, we could assume that the presence of a pedestrian is likely.

In a second category, we consider active and passive sensors, capturing most points in a vehicle’s surrounding, as exemplified in Fig. 3, namely: vision, LIDAR, and RADAR. Vehicles equipped with vision sensors, with embedded streaming capabilities are becoming commonplace. Thereby, setups are mainly based on mono, stereo, infrared/thermal cameras. Note that mono- and stereo cameras offer a high resolution, however are subject to environmental influences, while infrared/thermal work well at all lighting/ weather conditions and raises less privacy concerns. While vision sensors can be mounted at multiple locations (e.g. roof, side), the forward-facing or surrounding-view cameras are used to identify active modes and objects in the field of view, by creating a composite picture of the surrounding environment. Large improvements in computer vision based pedestrian detection were made in the recent past [11], [14]. LIDAR provides highly accurate long-range object detections (up to 250m), by continuously scanning the environment. They are usually mounted to the top of a vehicle, and compared with cameras can provide accurate information and larger field of view (i.e. unobstructed 360-

degree view) [41]. While LIDAR exist at different wavelength and resolution, high-resolution LIDAR are able to pinpoint pedestrians at high accuracy and make it even possible for the system to detect human poses. RADAR in contrast, output distance, velocity, and typically have high measurement accuracy. Typically, 360-horizontal coverage using short-range radars ($\sim 40\text{m}$ range) and mid-range-radars ($\sim 100\text{m}$ range) can be achieved with 4-6 radars mounted at each corner/side of the vehicle. As RADAR is less affected by external conditions, they provide redundancy for camera and LIDAR.

The detection accuracy and correct localisation can be significantly improved by fusing data from a set of sensors. This for instance, supports the use of a sensing network with multiple sensors, while making use of vehicles’ movements to increase detection and measurement performance through the extension of different field of views. This capability that provides depth perception of the surrounding environment is likely to become pervasive in future vehicles. Note that the mentioned sensor components all depend on different system integration and amount of processing.

B. Active mode sensing scenarios

We further give an overview of urban traffic situations, illustrated in Fig. 4, where pedestrians and cyclists can be sensed with AMSense. Four situations are used to describe specifics on interactions between mobile sensing platforms and active mode behaviours in a set of generally representative urban traffic settings: a) target is in field of view, b) is not in field of view, c) unclear situations due to occlusion, and d) the target deviates from his linear trajectory (e.g. crossing). Note that we assume active modes not to be restricted by the pedestrian or cyclist network (e.g. shared spaces), while vehicles to only use the underlying street network.

A pedestrian or cyclist may be identified or tracked in time and space by one or more sensing platforms. However, when assigned an ID (e.g. “pedestrian 1”) and tracked for a certain time interval, the tracked target may loose its temporary ID in situations where no target-sensing is possible (e.g. occlusion, location not sensed). The target will most likely be assigned a new ID, when reentering the field of view of that same (or different) vehicle. While a vehicle sensing a target can solely be expressed as the estimate detecting that target, the quality of collected data depends upon the interplay of the sensing system’s technological capabilities and actual urban traffic conditions. Overall, the granularity and accuracy of the data are typically determined by sensor types, while the accuracy also depends upon sensing positioning, node coverage and external conditions (e.g. weather).

In the first scenario (a), the pedestrian and cyclist are in unobstructed field of view to their closest vehicle, and can thus directly be captured by that vehicle. This situation occurs when the target is in detection radius of the sensing vehicle, and in the case that no additional active mode, or object hinder a clear view on the target. In this situation we assume that data about that captured individual will always be available by means of at least one sensing vehicle, whether it is in motion or not. Collected information about that pedestrian/cyclist could therefore

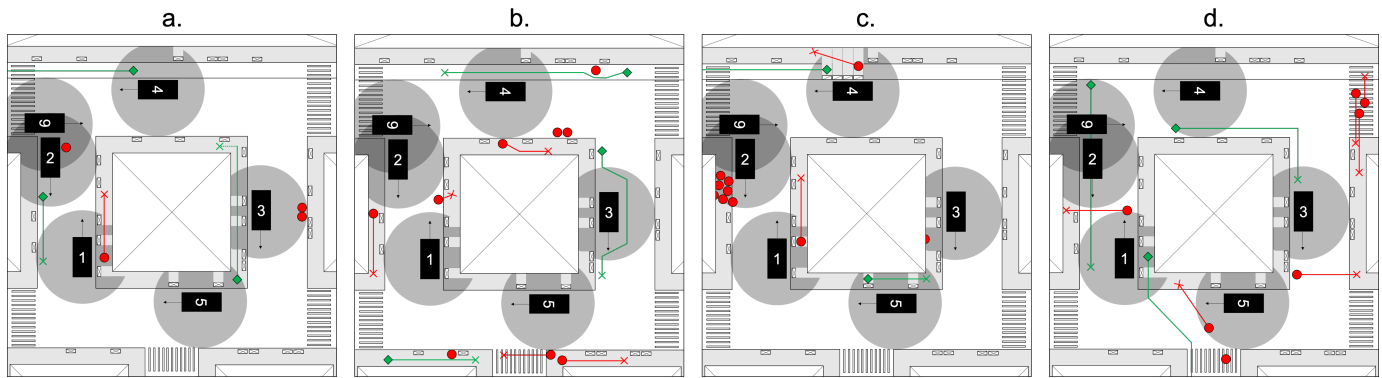


Fig. 4. Overview of potential traffic situations, where mobile sensing platforms sense their environment while pedestrians (red circles) and cyclists (green diamonds) are a) in field of view, b) not in the field of view, c) not or partially detectable, d) crossing.

include presence, locations, speeds, and movements, generated at each sampling time until moving out the detection radius. The measurement accuracy of that individual, is affected by the sensing vehicle’s position, that is the distance and angle to the target. Furthermore, the effects of such sensing network on data quality becomes apparent when an active mode is captured by more than one sensing platform, as in Fig. 4 vehicles 2 and 6. Both generated data are fused (data needs to be fresh), extending the vision on that pedestrian while potentially increasing the accuracy and granularity of the data.

In a second scenario (b), the pedestrian and cyclist are in unobstructed field of view to their closest vehicle, however can’t be directly captured as they are not inside the vehicle’s detection radius. This situation occurs in case of large distances or wide angles between the target and sensing vehicle. In this situation no data on the present active modes is generated. Although vehicles may sense their surroundings, no pedestrian/cyclist is detected until they reach one of the vehicles’ sensing radius. Yet, prior data that was generated at the time a pedestrian/cyclist was moving in a vehicle’s sensing radius, might still be available in the network (e.g. data storage). Almost fresh information (e.g. near real-time) may then be used to estimate an active mode’s position for a limited time interval. This situation can be altered by increasing the coverage of that sensed area.

In a third scenario (c), the pedestrian and cyclist are in obstructed field of view to their closest vehicle, and thus can’t be sensed by that vehicle, in the time of sampling. This situation occurs when an object (i.e. infrastructure, nature) hinders the view, and thus makes perception of the active mode impossible, even though the target is in radius of detection. This situation also occurs in settings where crowds make individual detection more difficult. Full occlusion entirely hinders collecting any data about that individual’s presence, location, speed, or movements, until reappearing in the same (or another) vehicle’s field of view. Partial occlusion, yet, reduces dramatically the quality of data, however, data about that active mode may be processed up to a certain extent. The positioning of a mobile sensing platform and its sensors influences the occlusion shadow, and therefore, the amount of collected information. Thereby, data fusion enhances the

overall detection and perception, as diverse sensors could capture targets differently. At the same time, increasing the sensing coverage, is likely to expand the collective field of view on a scene.

In a fourth scenario (d), we show a subset of different crossing situations in urban traffic settings. Active modes may use signalled or unsignalled locations to cross a street. Involved vehicles adapt their ego-motion to the crossing situation, which shall have no effects on sensing capabilities. However, less vehicles might be able to see that crossing individual as they’ll have a different perspective on the environment (parallax), e.g. crossing in front of a vehicle create an occlusion shadow for the following vehicles. Remember that perception data from the first vehicle can then be used to extend the field of view of following vehicles.

The quality of collected data is, technological capabilities and external conditions aside, mainly influenced by the positioning of sensing vehicles to their targets, as well as the sensing coverage at a certain location. Likewise, the movement of pedestrians and cyclists is equally influencing the collection of data quality, due to occlusion introduced by infrastructure, vehicles or groups of people. In addition, the movements of vehicles in relation to a sensed radius influences the granularity of the data. Remind that, collecting datasets about labeled individuals across the network, as for instance needed in route choice studies, seems impossible without using additional sensing technologies (e.g. Bluetooth).

C. External operating conditions

Although we cannot account for all environmental factors that might affect the sensing performance, we describe the ones that are most likely to adversely affect the correctness of sensors, protocols, and algorithms. In the remainder of this section, we describe weather effects, occlusion effects, and noise model.

In addition to dealing with internal system failures resources (e.g. bandwidth), the mobile sensing network, and more particularly single sensor nodes may fail or be blocked due to physical damage, or environmental interferences. Environmental reliability, denoted as $R_k(t)$, can be modelled using the Poisson distribution and represents the probability functioning

without interruption during sampling time t . Furthermore, weather conditions (e.g. low visibility), can directly affect the active mode detection, and cause false positives/negatives. In scenarios with low lighting conditions, we expect a drastic decrease in sensing performance of most vision sensors (infrared excluded). Temperature is not expected to have a direct effect on overall performance.

Road conditions (e.g. street quality) and the presence of obstructing infrastructure or urban greenery can have a negative impact on the quality of sensing targets and communication between nodes. One of the main concerns when detecting pedestrians and cyclists is occlusion, which occurs especially in high density scenes or when objects hinder a clear view in an observed area. A vehicle's field of view towards the sidewalk may be occluded by trees, parked cars or urban infrastructure. This prevents the mobile sensing platform to correctly observe the actual scene, and thus missing out possible pedestrians (or cyclists). Although some areas might present high risk of occlusion, this occlusion might not be present for very long since the active modes and sensing vehicles are moving at different relative speed. In an eventual future, in which one could think of vehicle manufacturers or fleet operators allowing the placement of sensors at various locations on a vehicle, the surrounding environment could be perceived from a multitude of distinct points on a mobile sensing platform. It should be noted that vehicle-free areas make up a sizeable fraction of most urban areas. Active modes would therefore have to be monitored with other mobile vehicles (e.g. bikes, drones), or static sensors that are equivalent to mobile sensing platforms at speed 0, and their fusion would be worth considering in future studies.

Typically, such a mobile sensing network is subject of noise-corruption that increases with the quantity of sensor nodes involved. As mentioned earlier, the detection of a pedestrian/cyclist is only expressible as a probability. All raw sensor data come with uncertainties (i.e. sensor efficiency, weather, road conditions) and hence inherit noise. Probabilistic methods, such as Kalman filter, addresses this margin of error.

VI. CONCLUSION

In this paper, we presented AMSense, a novel mobile sensing system that uses connected multi-sensor equipped vehicles to build a sensing network which captures pedestrians and cyclists spatiotemporal properties in urban areas. The collected data about pedestrian/cyclist presence, locations, and movements can be used as input for a variety of studies that require active mode information at diverse macro- and microscopic levels. Future work will dig into challenges of reliability, scalability, as well as ethical, privacy, and security considerations. Moreover, future work will investigate dynamic and context-aware data collection, explore the potential of measuring spatiotemporal densities, speeds and flows using such a mobile sensing system, and study active repositioning of sensing vehicles to optimise vehicle allocation.

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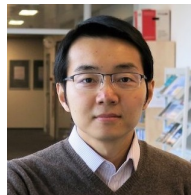
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Alphonse Vial is currently working towards his PhD degree with the Department of Transport and Planning, Delft University of Technology, The Netherlands. He completed prior engineering degrees (B.Sc. and M.Sc.) in Germany, France and Switzerland. During that time, he was a visiting student and research fellow with Massachusetts Institute of Technology, Fraunhofer Institute, ETH Zurich and Daimler AG. His current research interests lie in the broad areas of intelligent transportation systems, sensor networks, big data analytics, and mobile cyber-physical systems. Stevinweg 1, 2628CN Delft, The Netherlands. a.a.vial@tudelft.nl



Winnie Daamen is currently an Associate professor in the chair of Traffic Operations and Management of the Department of Transport and Planning, Delft University of Technology, The Netherlands. Her research interests include theory, modeling, and simulation of traffic (pedestrians, cyclists, vehicles, and vessels). The core of her expertise is in data collection, data analysis to get insight into traffic participant behavior and modelling these behaviors. This does not only involve pedestrians, but also cyclists, drivers and the bridge team of vessels. Stevinweg 1, 2628CN Delft, The Netherlands. w.daamen@tudelft.nl



Aaron Yi Ding is a tenure-track Assistant Professor in the Department of Engineering Systems and Services at TU Delft. Prior to TU Delft, he has worked at TU Munich in Germany, Columbia University in USA, University of Cambridge in UK and University of Helsinki in Finland. He obtained MSc and PhD both with distinction from the Department of Computer Science (Birthplace of Linux) at University of Helsinki. His research focuses on edge computing, IoT and mobile networking services. He is a two-time recipient of the Nokia Foundation Scholarships, and is awarded the Best Paper of ACM EdgeSys 2019 and the ACM SIGCOMM Best of CCR. Stevinweg 1, 2628CN Delft, The Netherlands. aaron.ding@tudelft.nl



Bart van Arem received the M.S. and Ph.D. degrees in applied mathematics from the University of Twente, Enschede, The Netherlands, in 1986 and 1990, respectively. From 1992 and 2009, he was a Researcher and Program Manager with TNO, working on intelligent transport systems, in which he has been active in various national and international projects. Since 2009, he has been a Full Professor of Intelligent Transport Modelling with the Department of Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands. His research focuses on modelling the impact of intelligent transport systems on mobility. Stevinweg 1, 2628CN Delft, The Netherlands. b.vanarem@tudelft.nl



Serge Hoogendoorn is currently a Professor and the Head of the Chair of Traffic Operations and Management, Department of Transport and Planning, Delft University of Technology, The Netherlands. He is also a Principal Investigator with the AMS Amsterdam Institute for Advanced Metropolitan Solutions, The Netherlands, a Faculty Fellow with the IBM Benelux Center of Advanced Studies, The Netherlands, and a Strategic Advisor with ARANE, The Netherlands. In the past five years, his research has involved theory, modeling, and simulation of traffic and transportation networks. He focused on innovative approaches to collect microscopic traffic data and the use of these data to underpin the models and theories that he have developed, using new techniques for model identification. Stevinweg 1, 2628CN Delft, The Netherlands. s.p.hoogendoorn@tudelft.nl