Chapter 11

Sensing Human Activity for Smart Cities' Mobility Management

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Additional information is available at the end of the chapter

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Abstract

Knowledge about human mobility patterns is the key element towards efficient mobility management. Traditionally, these data are collected by paper/phone household surveys or travel diaries and serve as input for transportation planning models. In this chapter, we report on current state-of-the-art techniques for sensing human activity and report on their applicability for smart city mobility management purposes. We particularly focus on the use of location-enabled devices and their potential towards replacing traditional data collection approaches. Furthermore, to illustrate applicability of smartphones as ubiquitous sensing devices we report on the use of Routecoach application that was used for mobility data collection in the city of Leuven, Belgium. We provide insights into lessons learned, ways in which collected data were used by different stakeholders, and identify existing gaps and future research needs in this field.

Keywords: smart cities, travel behavior, travel patterns, data collection, GNSS, call details records, crowdsourcing, smartphone, sensing human activity, transportation planning

1. Introduction

The topic of smart cities gained increasing interest among researchers from different fields. The concept goes beyond the pure use of information and communication technologies (ICT) towards building smarter buildings, mobility solutions, sustainable living and smart governance that meets the needs of an urban population as a sustainable community. In this chapter, we examine the role and potential of sensing devices as one of key pillars towards smart mobility management. We particularly focus on the use of smartphones as ubiquitous sensing devices that provide more detailed insight into mobility behavior than ever before facilitating smarter mobility management, development of tailor made policy measures and advanced two-way communication channels between relevant stakeholders. To illustrate these potentials we report on the use of Routecoach app developed at Ghent University and used by more than 8000 users for mobility data collection in the city of Leuven, Belgium. We provide insights into lessons learned, ways in which collected data were used by different stakeholders, and identify future research needs that can alleviate existing gaps towards truly smart and seamless mobility management.

2. Sensing human activity

Understanding mobility behavior is one of the key elements in ensuring better transport and urban planning. Advances in these areas are welcomed as they can ensure more seamless mobility, which is particularly a demanding task in urban areas where different transport modes meet and often share same space. As mobility is service, and it is impossible to store its capacities at certain location for future time, when the service will be needed, but rather synchronized time-space respond to dynamic demand is needed. To be able to better estimate these demands, and provide adequate level of service, data on travel activities are collected. The traditional data collection process can be user-oriented or location-oriented.

2.1. User-oriented sensing

A user-oriented approach goes from starting point of mobility system's user and data collected this way are usually aggregated at the household level. This type of data collection process commonly involves implementation of paper or phone household surveys, or interviews, where people are asked to record or state their travel behavior on for instance an average weekday. Ideally, household travel surveys involve representative sample of target population, and processed data on trip origins and destinations, frequencies, purposes, and utilized transport modes serve as an input for transportation planning models. Ettema et al. [1] and Stopher and Greaves [2] have shown that data collected in this way deviated systematically from the actual travel behavior. Some examples of such deviation include tendency of the respondents to underreport non-motorized trips [3–5] or public transport users to overestimate their actual travel time [6]. Furthermore, response rates to these surveys tend to be low which represents challenge in terms of nonresponse bias [7]. To avoid these pitfalls paper travel diaries were introduced [8].

In paper travel diaries, one is asked to systematically note his or hers travel behavior details with respect to travel times, origin and destination locations, transport modes, trip purposes, and frequencies. The data collection interval is usually one complete week during non-holiday periods. Literature reports [9, 10] that respondents tend to postpone filling in these diaries, which results in obtaining incomplete and inconsistent information. Quite often this would include having trouble remembering and recording smaller trips (e.g., walking to nearby post office to pick up package delivery or to local library to return a book), rounding off time and

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distances [11], having difficulties in defining the exact locations of places they have visited, or underreporting multimodal trip segments (e.g., indicating trip made by public transport, but forgetting to mention walking to and from public transport stop or between metro and bus stops).

Indeed, both travel surveys and diaries were designed primarily to provide data for macroscopic traffic models, and respectively, were focused on capturing trips between traffic analysis zones (TAZs). A TAZ is the unit of geography most commonly used in conventional transportation planning models and represents spatially homogeneous land use area (e.g., residential area, industry area etc.). Size of the TAZ varies, but typically it is a zone of under 3000 people. Quite often, these zones match census block information which makes it easier to interpret models' outputs. As macroscopic traffic models are not focused on trips inside individual TAZs, but between different ones, both travel surveys and diaries ignored shorter trips within TAZs and, this way further impacted underreporting of smaller trips that were usually made by active transport modes [12, 13]. This resulted in bias in observed modal splits and further underpinned evolution of car-oriented transport.

2.2. Location-oriented sensing

Compared to user-oriented sensing, the location-oriented data collection process tries to capture travel entities that are passing predefined location. This can be one point in the transport network, but more often the data collection process includes several points dispersed geographically to cover target area and all input/output points to the target part of the network (e.g., main roads entering the city, train stations etc.). The most straightforward way is to manually note the number of vehicles or pedestrians that passed the predefined location within the predefined time interval (usually 15 min or 1 h). In addition, other traffic data like, vehicle occupancy rate or vehicle classifications can also be collected. As manual counting is quite expensive way to collect mobility data and suffers from human errors, this approach is further developed into automated counting of moving objects. For this purpose, different types of a data recorders and sensors placed on or under the traffic network surface can be used (e.g., pneumatic road tubes, piezoelectric sensors and inductive loops). This has been widely deployed over the past few decades but the implementation and maintenance costs tend to be high. In addition, they successfully extract only traffic counts while additional information stay unreported (e.g., vehicle occupancy rate). To avoid these pitfalls, video based techniques for traffic counting have been developed. They rely on vehicle identification and more advanced approaches can include automated vehicle classifications or capturing of vehicle occupancy rates.

2.2.1. Computer vision applications

For vehicle identification, usually license plate matching techniques are applied. These techniques consist of collecting vehicle license plate characters and arrival times at various checkpoints. Since manual collection of license plate information is less practical for high-speed roads, ideally this is done by video cameras and character recognition software to recognize and automatically transcribe the license plate number for subsequent computer processing

[14]. Collection of arrival times at different checkpoints makes it possible to process data in order to recreate vehicle movements (if data collection points are of adequate density) or to derive travel times in the transport network. However, the ability of video based method to correctly identify license plate characters is often influenced by factors such as vehicle speed, volume of vehicle flow, ambient illumination (day, night, sun, or shadow), spacing between vehicles (occlusion), weather conditions (rain, snow, fog), plate variety, physical position of the plate (tilt, rotation), etc. In general, the license plate capturing and recognition rates may vary from as low as 15% (for poor visibility/weather conditions) to as high as 85–90% [15]. Another application for mobility studies comes from the possibility of implementation of computer vision applications in vehicles to recognize the surroundings and adjust their driving behavior in line with this information. These types of applications are particularly interesting for automated vehicles as future mobility entities within the smart cities. **Figure 1** shows example of ongoing research activities under the Vebimobe project where applicability of computer vision for automated recognition of traffic signs within the city of Ghent, Belgium is studied. Specially designed vehicles test the ability to recognize traffic signs, while being integrated in traffic flow movements, from cameras that operate in different spectrums [16]. One of the main aims of the Vebimobe project is to examine readiness of related technologies in ensuring application of such data collection techniques for automated vehicles' speed adaption and more sustainable route guidance applications.

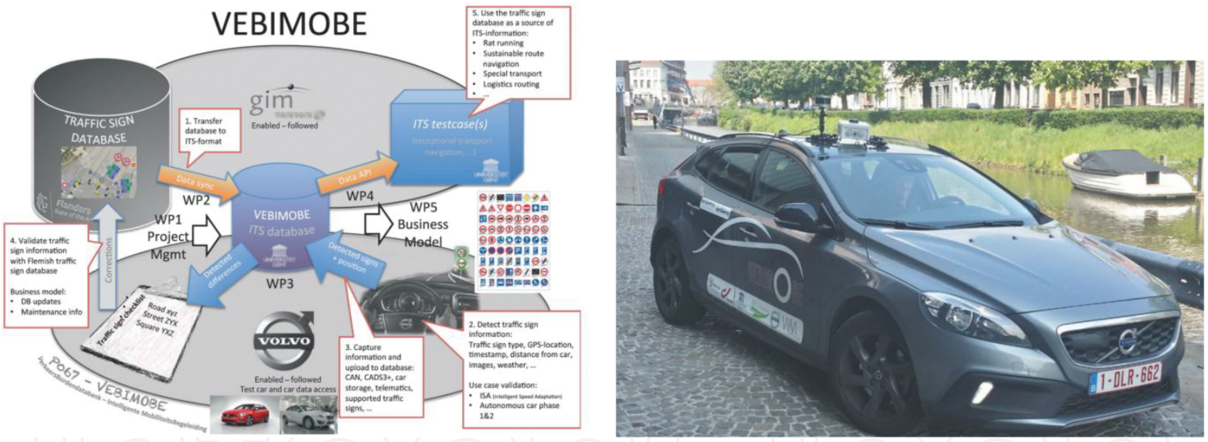

Figure 1. Vebimobe —organization structure of research activities (left) and test vehicle with equipment for computer vision supported detection of traffic signs (right) (from [16]).

Furthermore, for machines to be able to detect and identify people instead of vehicles (or traffic signs) is a more challenging task and sensing of humans has long been one of the hardest machine vision problems to tackle. Next to the inherited challenges with ambient illumination, occlusions (e.g. having umbrella), weather conditions (rain, snow, fog), etc., main challenge comes from wider diversity in appearance and more erratic way humans behave. So far successful applications mainly focus on recognizing human silhouettes and classifying activities (standing, walking) [17, 18] while face recognition performs better on a smaller scale. For urban areas where large number of people passes daily (e.g., in a train station), the performance is lower due to limits in recognition. However, for mobility-related applications where just separation between different transport modes is needed (in this case, just recognizing whether it is human/pedestrian), success rates are higher than in case where actually identifying a unique human is needed to, for example, compare travel times between successive locations.

2.2.2. Bluetooth scanning

More recently, Bluetooth has been suggested as an interesting alternative for location oriented sensing technology. Bluetooth is a wireless technology standard [19] for exchanging data over short distances. It uses short wavelength ultra-high frequency (UHF) radio waves in the industrial, scientific and medical (ISM) band from 2.4 to 2.485 GHz [20]. It was invented by telecom vendor Ericsson in 1994, and it can connect several devices, overcoming problems of synchronization which makes it particularly interesting for implementations ranging from fixed and mobile devices to building personal area networks [20]. Prior to the wireless connection of two devices through Bluetooth, the inquiry phase of the protocol needs to be completed. In this phase, an initiator device initiates the service discovery procedure by transmitting inquiry packets. Devices, that allow themselves to be discoverable, issue an inquiry response. The inquiry response includes information on device ID (48-bit identifier of the mobile device—MAC address) and clock [21]. The interesting feature, for mobility studies, is that these information are exchanged before any connection is established which allows completely unobtrusive sensing of nearby devices.

Today, Bluetooth has become an almost ubiquitous technology on modern mobile devices and private vehicle keys, by placing static Bluetooth sensors at strategic locations one can get insights into personal (based on mobile devices) or vehicle (based on keys) mobility in a variety of contexts. Due to the range limitations this technology is more appropriate for location-oriented tracking than user based one, but with additional processing user trajectories can be approximated based on the timestamp sequences. Phua et al. [22] have compared Bluetooth sensed data at supermarket and manually measured data using systematic sampling and found that trip lengths and user demographics were similar with the exception of underrepresenting older population. Other examples of sensing human mobility include travel time measurements of motorized traffic [23, 24], tracking of pedestrians [25], mobility-related incident detection [26, 27], dynamics at mass events [28] and others.

Figure 2 shows implementation of Bluetooth scanners for monitoring the crowd behavior during the Ghent Festivities in Ghent, Belgium (as described in [28]). Implementation aimed at supporting city event management for the organization, security, transport, and emergency service providers. Ghent Festivities take place, every year at the end of July, on 11 squares in the city center and lasts one full week (including both starting and ending weekends). Squares, and city itself, act as major attractions during this period hosting on-stage performances, food stands, and fairs that attract around two million people during festivities. On this occasion, 22 locations were covered with Bluetooth scanners. Collected data represented people's mobility within the festivity zone itself and the mobility to and from the festivity zone. Applications of the resulting data are manifold. The most direct result are the statistics about visitors and their sensed behavior (e.g., the number of visitors per day, the time and space distribution of visitors, the (sequence of) squares visited by individual visitors, etc.). A second, derived set of results deals with the distribution and dynamics of the crowd in the festivity zone and the city center. This information is vital for security services, which are monitoring the people density in order to plan safety measures as temporary closures of access to overcrowded squares or facilitating the circulation between certain festive locations. Derived information is also made available to visitors by the festivity app, assisting them to plan their visit avoiding overcrowded or temporary closed areas. A third set of results deals with the accessibility of the festivity zone and is derived from monitoring of the travel times between train stations, public transport stops, park and ride locations, and the festivity zone. For example, by analyzing sequence of Bluetooth scans, of the same IDs, starting from the park and ride facility towards the city center prolonged travel times can be observed. This suggests congestion problems on the route, where traffic police should intervene to facilitate the circulation of the public transport. This way, the sensed data assist partners to optimize safety and comfort to the visitors of the festivity [30].

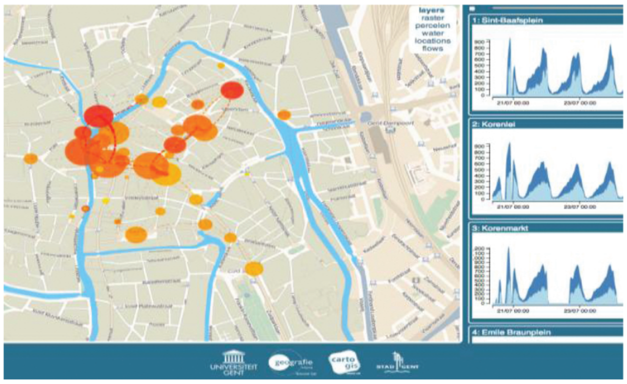

Figure 2. Bluetooth scanning implementation for mass events (Ghent Festivities event in Ghent, Belgium) [29].

The given example, illustrates the potential of using Bluetooth scanning for deriving origin and destination locations within the city or travel times. However, Bluetooth sensed data for mobility studies exhibit several limitations. First, sensed location is limited to the selected locations of static Bluetooth scanners. By analyzing sequence of observed devices' IDs between different locations, movement data can be estimated but exact paths are unknown unless Bluetooth scanners are placed at each intersection of the transport network. However, this might be quite expensive especially in large networks. Second issue is related to sample sizing and data quality. As only the activity of discoverable Bluetooth devices can be sensed, to report on the population level (e.g., absolute density or flow statistics) ratio of discoverable Bluetooth devices across general population needs to be determined. This is mainly done based on the manual counts of the total number of visitors at sensing locations; however, this process tends to be expensive.

Overall, when analyzing the implementation potential of location based sensing techniques for mobility studies, main limitations come from need for higher level of details, insights into utilized network connections and traffic flows dependencies, as well as need to include all users of the mobility network (pedestrians, bicyclists, public transport users, etc.). All of the location based sensing techniques score well for some of these challenges but fail at others. For example, sensors placed on or under the traffic network surface provide confident counts of vehicles, but cannot identify individual moving objects and therefore compare its observations across different locations. Computer vision based applications, have higher success rates in distinguishing between different transport modes, but still have limited success in identifying individual moving objects for practical implementation. Bluetooth sensors can easily identify individual devices and based on this information, track their moving sequences between different locations, but they require high density of sensing locations to reconstruct actual paths and cannot provide vehicle counts with same accuracy as road sensors or confident estimation of used transport modes.

2.3. Location-enabled devices

Introduction of location-enabled devices started an important revolution in mobility studies [31–34] as they allowed continuous tracking of movement locations and, this way, were able to fill some of the gaps that were present when collecting data using traditional methods [35–37]. Location-enabled devices mainly relay on global navigation satellite system (GNSS). The GNSS refers to a constellation of satellites providing signals from space transmitting positioning and timing data and, by definition, it provides global coverage. The GNSS allows small electronic receivers to determine their location (longitude, latitude, and altitude) to high precision. The signals also allow the electronic receiver to calculate the current local time to high precision, which allows time synchronization. Examples of GNSS include USA's NAVSTAR Global Positioning System (GPS) and Russia's Global'naya Navigatsionnaya Sputnikovaya Sistema (GLONASS) [38–40]. Europe is in the process of launching its own independent GNSS, Galileo, and China is currently expanding its regional BeiDou Navigation Satellite System into the global Compass navigation system [41]. First location-enabled devices that were used for mobility studies were usually installed in vehicles (**Figure 3**). Data collected in this way were used to note travel times [42, 43], detect congested segments in traffic network [44, 45], or reconstruct vehicle trajectories [46, 47]. Cai et al. [48] and Gullivera et al. [49] developed road traffic noise estimation models based on the collected GNSS data. Ćavar et al. [50, 51] used GNSS vehicle tracks to develop machine learning based model for predicting travel times in urban areas.

When collecting data on traffic stream for intelligent transportation system (ITS) applications, vehicles equipped with location-enabled devices are classified based on the vehicle driving styles as (a) average car (vehicle travels according to the driver's judgment of the average speed of the traffic stream); (b) floating car (driver "floats" with the traffic by attempting to safely pass as many vehicles as pass the test vehicle) and (c) maximum car (vehicle is driven at the posted speed limit unless impeded by actual traffic conditions or safety considerations). The information on the applied driving style is crucial for correct interpretation of the collected data and development of derived statistics. In the literature, the most often applied style is floating car [52, 53] as it has been seen to provide the most representative description of the actual traffic stream. However, since GNSS devices for mobility studies were usually installed in vehicles, consequently they only tracked a small portion of mobility behavior (i.e., car trips).

To track the full spectrum of mobility behavior, respondent needed to carry the handheld GNSS-devices continuously, as forgetting it would result in unreported gaps in the trip data [54]. This requires significant effort and discipline from the respondent. Furthermore, to be able to evaluate success rates of such data collection procedures, respondents often needed to note their trips manually which, together with carrying the device, represented significant burden to the respondents.

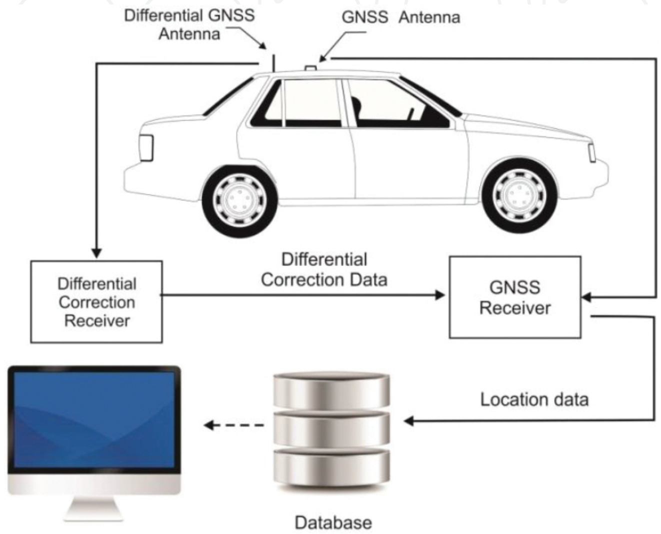

Figure 3. GNSS equipped vehicle (based on [15]).

2.4. Smartphone based crowdsourcing for mobility studies

Advances in development of GNSS chipsets allowed their integration in small devices, like smartphones, which resulted in emerging new possibilities for mobility behavior sensing. Carrying a smartphone has become a habit, and is therefore considered less of a burden, reducing the risk of non-reported trips. In addition, smartphones today have the same capabilities as the portable GNSS-device but also include additional sensors which can offer a more solid base for required interpretations of the data (e.g., use of accelerometer to determine the travel mode) and improve location precision.

In general, we can distinguish three ways in which mobile phone data are sensed for mobility studies (1) call detail record and network signalization data; (2) ″passive″ tracking and (3) ″active″ or ″interactive″ tracking.

2.4.1. Call detail record and network signalization data

Call detail record and network signalization data represents standardized data, collected by mobile network operators for billing purposes. Such data include records of all user-initiated activities such as calls, SMSs, internet, and data services where each record includes spatial and temporal parameters. In addition, network data include regular location updates of mobile devices, usually collected every hour, or every three hours, depending on the network generation and configuration. Handing over details (records created when user moves from area covered by one base station to another) are also noted. Therefore, frequency of the collected data varies depending on the device, network, and user activity. The location information is approximated to the telecom operator's base station points. The base stations (**Figure 4**) are land stations in the land mobile service that provide the connection between mobile phones and the wider telephone network. The size of area that each base station covers (and respectively, the distance between base stations) is not fixed and is a result of the trade-off between number of users (generated traffic), available frequencies, and quality of the service that operator wants to ensure. In practice, this results in a higher density of base stations in urban areas and lower in rural areas, but it is additionally influenced by build-up area and land configuration, as well as with specific user movement patterns in the vicinity of the base station (e.g., base stations that cover highways will have directed antennas, to ensure as little as possible handovers, and area that they cover will have highly elongated shape (**Figure 4**)). For these reasons, it is expected that location precision will be lower in rural areas and along high speed roads (**Figure 5**).

Figure 4. Base station (from [55]).

International telecommunication union reported 12-fold increase of penetration rates for mobile, and smartphone devices, since 2007 [56]. Such growth means that for the most of the areas (especially in developed countries) these data are capable to represent overall population movements. This potential gained much attention over the past years. Eurostat investigates possibility to replace some of the traditional data collection methods for general statistics with the use of call detail record and network signalization data [57–59]. Furthermore, their applicability in the scope of mobility studies has been investigated for rush hour analysis [60, 61], detection of variability in human activity spaces [62–64], correlation of mobility behavior with land use [65], and detection of TAZs and origin-destination pairs [66, 67]. Lui et al. [68] investigate possibility to develop validation measures for activity-based transportation models from mobile phone records. For this purpose, they approximated daily "home," "other," and "work"-related travel sequences and classified them to define activity-travel profiles. By comparing profiles with travel survey statistics, they demonstrated validation potential of the call detail records for this purpose. Gao and Liu [69] used the clustering technique to identify whether different phones travel in the same vehicle. They used mobile phone data to determine speed, vehicle counts, type, and density. This approach showed potential to be used for estimation of vehicle occupancies rates although manual counting would be needed to evaluate its effectiveness. Furthermore, Chen et al. [70] compared handover location updates and regular network based location updates to estimate travel speeds. AbdelAziz and Youssef [71] and Wang et al. [72] examined possibility to detect the transport mode one is using from their call detail record and base station location data.

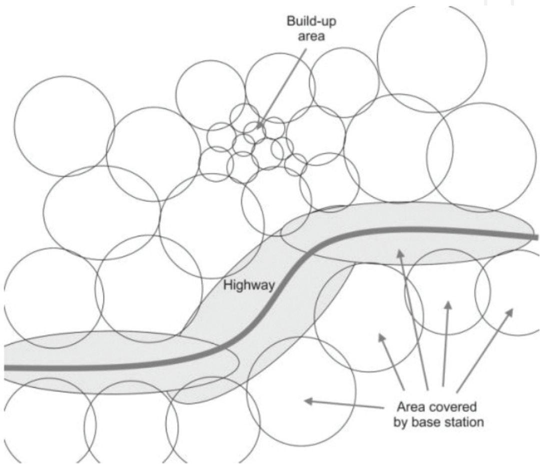

Figure 5. Base stations coverage.

At this point, all of the mobility-related studies that have examined possibility to use call detail record and network signalization data for analyzing the human travel behavior recognize high potential these data have for future applications. However, success rates achieved with processed data are still unsatisfactory for their practical implementation. Potentially, the largest limitation, in this sense, comes from low location precision (limited to cellular network base station locations) and time resolution (limited to users' activity or regular network location updates dependable upon the type/generation of the network). This makes these data more practical for extraction of origin and destination locations (which in this case would not overlap traditionally used TAZs but rather be based on the cellular network configuration) and crowd dynamics between different locations than for more detailed mobility studies. These solely are insufficient to replace traditional travel surveys but are a good starting point. Call detail record and network signalization data have a major advantage that comes from the fact that they are collected by all network operators, require no additional effort by users, no additional financial resources for their collection and cover wide areas, large populations and long time periods. On the other end, their usage for mobility, and other, studies at this point is hindered by a number of privacy and regulatory issues as well as some technological issues (e.g., how can the current data processing system be amended so that the processing of the mobile positioning data is also supported by statistical institutions), business related (e.g., operators see no benefits of providing data and, above all, are not motivated by possibility that concurrent companies have insights into their user base nor equipment locations), and methodological ones (e.g., the quality and applicability of the principles of statistical production in relation to mobile positioning data) [58, 73, 74].

2.4.2. "Passive" tracking

"Passive" tracking refers to the use of dedicated applications that run as a GNSS-based data logger in the background on the smartphone. Today, many applications collect such data (e.g., Google maps, Facebook, etc.). The use of "passive" tracked data is examined for the purposes of investigating individual mobility patterns [75, 76], speed analysis [77], traffic monitoring [78], or for large-scale sensing of human behavior for smart city-oriented applications [79]. Furthermore, smartphones are used as precise indoor positioning sensors in order to improve intelligent parking service [80] and as activity recognition sensors [81, 82]. Wan et al. [83] propose the use of mobile crowd sensing technology to support creation of dynamic route choices for drivers wishing to avoid congestion and Xia et al. [84] explore the use of smartphones, as sensors, for detection of transport modes from movement data of users.

The main advantage of this approach comes from higher spatial and temporal resolution of collected data than it is the case for mobile network call detail records. In fact, the spatial and temporal resolution of the collected data is set by the app maker itself, but can be influenced by user based on the mobile phone settings (e.g., positively by the use of GNSS, Wi-Fi and other network location data or negatively by simply turned-off mobile phone). Most often, the critical element in determining precision is the trade-off between phone's battery drain and data resolution. Foremski et al. [85] showed that smartphones can be used for crowd sensing with the decrease in battery lifetime by approximately 20%, which they found to be acceptable by users.

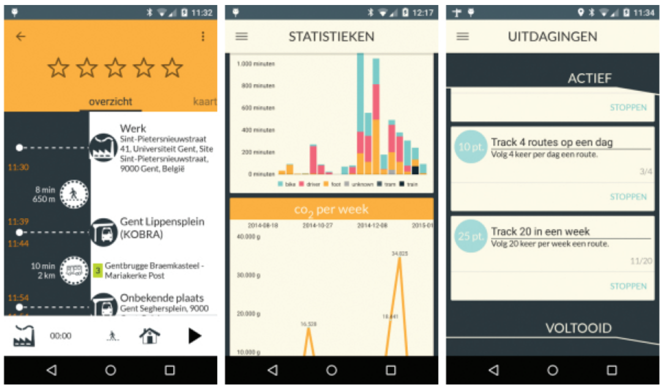

Figure 6. Routecoach — App.

Figure 6 shows Routecoach smartphone application [86, 87] that was developed at Ghent University [30] for collection of mobility data for the province of Flemish-Brabant in the frame of the Interreg IVb NWE project NISTO. The aim of NISTO (New Integrated Smart Transport Options) was to develop an evaluation and planning toolkit for mobility projects which is applicable transnationally and can be adopted by planners. The Leuven data collection process happened between January to April, 2015. In total, 8303 users actively participated by downloading the freely available application and collecting the data on one or more trips. Overall more than 30,000 trips have been recorded leading to about 350,000 km of recorded data (**Table 1**). The app had an option for ″passive″ data collection and ″active″ data collection (the ″active″ data collection segment of the app will be described in more details in the following section). **Figure 7** shows ″passive″ collected trips over the wider area of City of Leuven.

Variable	Value
Users	8303
Trips	30 000
Time period	4 months
GNSS points	3 960 234
km	340 000

Table 1. Sample descriptive data.

Figure 7. ″Passively″ logged trips (area: province of Flemish Brabant).

Applications of the resulting data are manifold. The most direct ones refer to user participation (e.g., general statistics) and mobility patterns (e.g., user activity). However, for detailed mobility studies significant post-processing is needed. This mainly refers to handling noisy data and removal of outliers. After data cleansing, map matching is required to match observed trips to the existing transport network locations. Care should be taken in this phase in order not to introduce errors by implemented map-matching algorithms and data quality control should be carried out with great care, as introduction of map-matching errors can lead to further errors in data interpretation and provide false base for mobility-related decision making.

Overall, main advantages of ″passive″ data collection, for mobility studies, compared to call detail record, come from higher spatial and temporal resolution. Compared to ″active″ tracking there is no need for interaction by respondents which reduces burden for the participant. That said, data collected this way require demanding data processing and interpretation efforts when compared to ″active″ tracking. Similar to call detail record processing advances, results of ″passive″ collected data processing are still not at mature level to replace travel diaries and surveys. One of the main challenges in this segment comes from the fact that it is hard to provide grand truth data, to ″passive″ logged data, and to check the success rates of the processing. As it is known that providing user with travel diary to note his trips will result in underreporting of small segments and trips made by active transport mode, these data are not applicable for representing the ground truth. In addition, the use of the apps is user initiated (user chooses to install, or not to install the app), whereas traditional data collection approaches were based on the initiative of the data collection institution. In this phase, data collection institution has an option to define representative sample and contact participants directly based on this definition. For mobile app data collection, it is challenging to determine the representatives of the sample as no background data are available about the user (e.g., no demographic data). It is always opted to aim for the law of large numbers, but aiming at mass data collection that would satisfy this condition would require substantial campaign resources and drastically increase the cost of data collection process. It is still to find the balance in this sense and tackle the question of crowdsourced data representativeness.

2.4.3. ″Active″ and/or ″interactive tracking″

"Active" and/or "interactive tracking" represents the use of interactive mobile applications where respondents can report additional trip data as the start of the trip or transport mode. Such reporting was, for instance, used to investigate the influence of carbon dioxide emission information on mode choice [88] and, mostly, as ground truth for the development of supervised machine learning models in order to replace parts of traditional travel surveys [89, 90]. Semanjski and Gautama [91] examined applicability of "active" sensed mobility data to predict what transport mode one will use for the next trip (**Figure 8**). They applied gradient boosting trees and achieved a success rate of 73% indicating that such data can be used for smart city-oriented mobility services as provision of transport mode relevant pre-travel information or different incentives in order to impact one's mobility behavior towards more sustainable mode choices.

The use of ″actively″ logged data is also explored in inferring transport modes from mobile sensed data. These approaches strongly relay on GNSS records [35, 77], but also include data from other smartphone sensors [92, 93]. In many cases, these data are fused so that the GNSS data are used to improve accuracy of, for example, accelerometer-based approaches, or vice versa [32, 70, 84]. On average, literature reports successful recognition between three to five transport modes by using around four indicators [35, 94]. Recognized transport modes mainly include: motorized transport (without separation between personal vehicle and, e.g., bus), bike and walking, and their recognition relies on variables as speed and acceleration, implying that they give the highest indication of a transport mode [84, 92]. The main challenge arises from similar speeds obtained by more than one transport mode (e.g., bike and pedestrians, or private car and public transport) which is only partially solved at this point and additional knowledge is still needed to increase the accuracies (which is mainly below 90%). Overall, all studies tested the proposed approaches on limited time span of collected data (ranging from four hours to one week) and limited number of participants failing to capture wide range of longitudinal, e.g., monthly or yearly, variations in travel behavior patterns. In addition, such short time ranges imply observed behavior under similar conditions (e.g., weather condition) where potential limitations might lie in terms of transferability of developed approaches on a wider population and/or area.

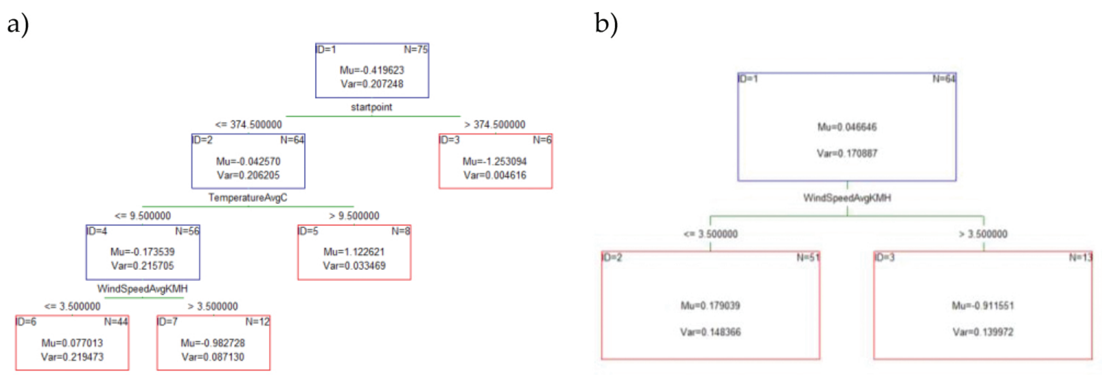

Figure 8. Decision trees for the transport modes (a) bike and (b) walk (from [89]).

For the Routecoach application, next to the "passive" logging that continuously tracked mobility behavior, participants were able to "actively" report and validate their data. "Active" data collection implied higher time-space resolution of the collected records and was initiated by the user. To start "active" data collection user needed to mark the transport mode used at the beginning of his or her trip. In addition, user was able to report the purpose of the trip, enabling extra contextual information. To reduce the burden to the participants, user-friendly graphical interface was developed so that users could simply switch between transport modes during their travels and, in this way, easily validate multimodal trips. To stop the "active" data collection user needed to mark end of the trip in the data collection app. In addition to the app, web interface was implemented (**Figure 9**) so that user can easily access personal mobility data (after the registration) and add or correct context of the trips (e.g., add purpose or correct wrongly introduced travel mode). In addition, web interface had incorporated web surveys that the user could fill in and provide personal information and insight into his or her attitudes toward different mobility options.

Data collected this way provide higher spatial and temporal resolution and rich (and validated) information on the context of travel activities. This significantly reduces need for data post-processing and allows relevant insights into mobility behavior. **Figure 10** shows Routecoach insights into observed delays at road network intersections in the city of Leuven, Belgium, providing local authorities with information on where to focus measures related to delay

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reductions. Insights on mobility behavior, at individual and aggregated levels, were also made available to the participants (personal data) and general audience (only aggregated results) so that everyone can adjust, if one wishes so, his or her behavior in order to avoid delays and crowded areas. High spatial and temporal resolution of data facilitated extraction of time relevant insights. Based on the crowdsensed data travel time for different transport modes could be observed and impact of newly introduced measures evaluated. For example, **Figure 11** shows bike travel time isochrones, where impact of new bike highway can be easily noticed in the North, and then North-East part of the network (as bike highway changes its direction). In addition, comparison of different transport modes is enabled as their performance can be simultaneously confronted. **Figure 12** shows accessibility of the main train station in Leuven during the afternoon peak hour. Blue area marks parts of the city from which it is faster to reach train station during this period than by car. Red areas indicate regions from which one would reach train station faster by car. These insights engaged citizens and policy maker into constructive discussion on mobility options and enable smarter mobility management.

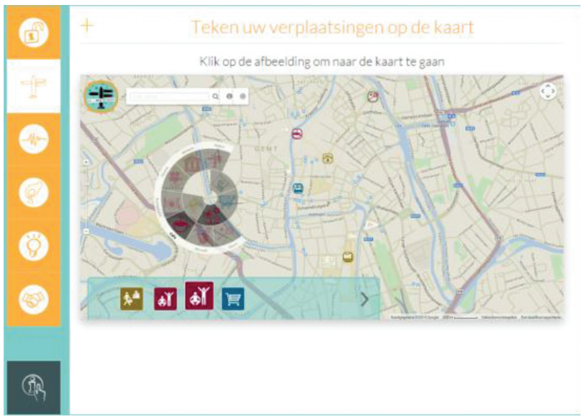

Figure 9. Routecoach – web interface.

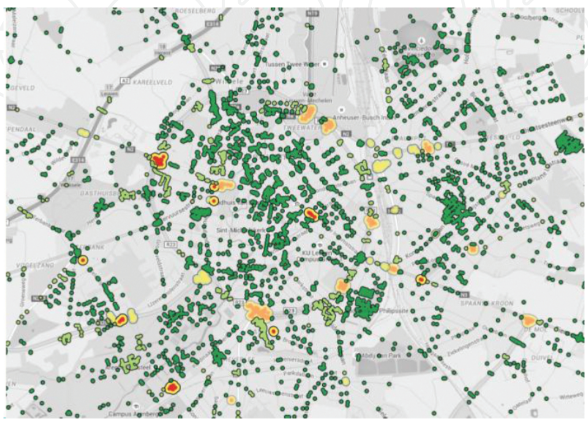

Figure 10. Delays at transport network intersections.

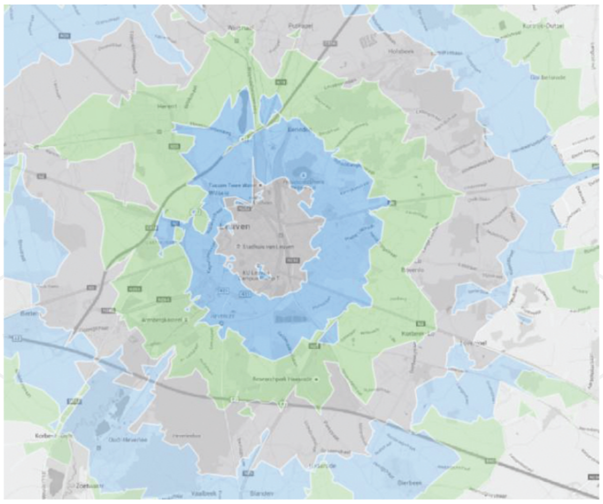

Figure 11. Bike travel time isochrones.

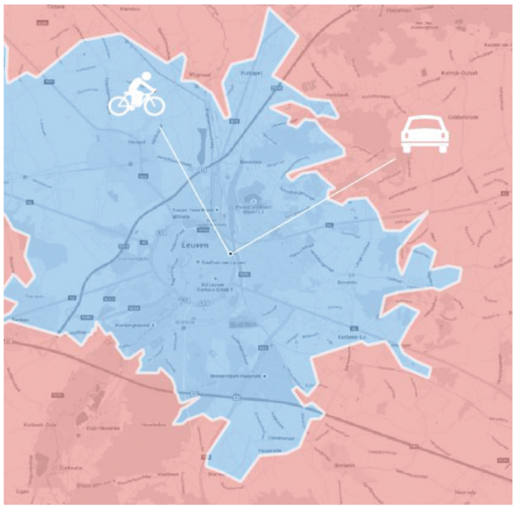

Figure 12. Accessibility of the main train station during afternoon peak hour.

Although "active" logging requires manual intervention by the respondent, this burden seems to be limited because the reporting is restricted to short entries at the very moment of departure and arrival. As a consequence, time and location of the departure and arrival can be more accurately detected, and there is no need for demanding data processing as splitting GNSS-based track into parts travelled by different modes [35, 95]. Overall, "active" data logging overcomes some of the weaknesses of call detail record and "passive" data collection approaches. For one, it provides trip context and reduces the need for extensive data post-processing. In addition, it also offers ground truth data for development of different machine learning based algorithms that can evolve towards the transport mode, or trip purpose, recognized from "passive" logged data. This way, more seamless transition from traditional data collection approaches, as travel surveys and diaries, towards fully data driven mobility management is facilitated. Another advantage comes from user validated data, and its potential to find balance between campaign expenses (to familiarize users with the data collection and app itself) and need for the representative sample, as based on the user provided personal information, one can extract representative subsample from the overall dataset. This can significantly reduce the cost of mobility data collection and creation of verified inputs for transport planning models. Compared to call details record, main advantages of ″active″ logged data come from higher spatial and temporal resolution. An example of this can be seen in quite demanding task to join data of lower resolution with, for example, freely available data on land use. Land use data have been often implemented to estimate trip purpose. Therefore determining whether trip ended at the school or office location is a quite challenging task, based on the call detail records, as within the area covered by one base station potentially there are both education, residential, work and commercial facilities. On the other end, the main challenge for ″active″ data collection comes from user engagement, trip reporting discipline, and motivation to participate in such activities. Although, users provide validated data on volunteering bases on same details as they were asked in traditional travel diaries, if existing, their privacy-related concerns need to be addressed. Transparent data processing and usage, as well as evident benefits in terms of better mobility management seem to be strong advocates for user motivation and participation.

3. Conclusion

The introduction of smartphones as mobility sensing devices exhibits multiple advantages when compared to traditional data collection approaches. It reduces the number of unreported trips which was the case for travel diaries and surveys where users often postponed completing these to later on during the day or week. This resulted in making it hard to remember short trips (e.g., walk to nearby restaurant during the lunch break). Regarding the mobility management, the above mentioned reflected as underrepresentation of walking and biking trips providing false insights into existing modal splits and supporting favoritism towards car-oriented transportation planning. In this sense, the use of smartphones can support more balanced sensing of mobility behavior across the use of different transport modes. In addition, as carrying a smartphone has become a habit for many people, the issue of unreported gaps in the trip data is overcome. Nevertheless the use of ″active″ logging for smart city-oriented mobility applications is advised as knowledge discovery from ″passive″ logged data remains unsatisfying (e.g., real time splitting of trips at transport mode changing points or estimation of trip purposes from ″passively″ collected data). This brings forward challenges related to respondents' motivation and participation in "active" logging. In this regard, the use of different incentives is still being researched [96]. So far, adjustable and personalized rewarding systems, social networks based interaction and gamifications show the highest potential. But, this area still remains to be further explored in order to relate these with different user profiles and balance between incentives and personal motivation. Regarding different user profiles, their role is of the most value when considering smartphones as tools for policy makers to deliver personalized mobility-related messages and make targeted policy measures. Psychological studies in this field suggest that profiling respondents based on their attitudes towards sustainable mobility options shows good potential in initiating behavioral change. In this context, smartphones can be used both as sensing devices and as two-way communication tools where targeted, time-space, relevant information can be delivered to users (e.g., reported estimated delays on the foreseen route of interest). This way, users can make more informed mobility decisions and information on observed behaviors can be integrated into advanced mobility management systems.

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