3 Tracking Urban Mobility

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Abstract

Within the coordinate reference systems discussed in the previous chapter, location can be described. Location data is increasingly becoming available from sensors integrated in urban mobility: sensors that are attached to travelers or vehicles, or even to fix locations registering travelers or vehicles passing by. This chapter will introduce some tracking technologies and their properties, and then define the notion of a trajectory, with its critical properties of spatial and temporal granularity (precision and sampling rate), and accuracy (linked to map matching). In addition, the chapter introduces the two complementary frames of references for tracking urban mobility, the Lagrangian and the Eulerian, and how to convert between them.

Keywords

Internet of things, IoT, location, tracking

3.1 Introduction

Tracking urban mobility is key to any smart interaction with mobility, inclusive of parking. Tracking relies on three components that must interact in some forms: something that moves, a sensor recognizing and characterizing this movement, and a connection of the sensor to some computing device, typically on board or through the Internet (Figure 3.1). The *moving object* can be, for example, a person in a market hall, tracked for his/her movement through a CCTV camera (the *sensor*), and their trajectory being analyzed for their shopping behavior in the marketplace (the *computing of information out of data*). As another example, the moving object can be a bus, equipped with a satellite positioning tracker, and the trajectory being sent to the operator for providing real-time arrival estimates on displays at bus stops. The same goal can be achieved by a parking sensor that senses whether a vehicle has moved into a parking slot and reports this information to a parking guidance system.

Of the three elements in Figure 3.1, the two yellow ones are usually subsumed as the *Internet of Things*. The Internet of Things is characterized by sensing and computing devices that are embedded in everyday objects, including mobile

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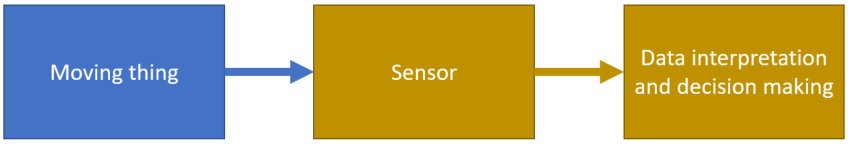

Figure 3.1: Something that moves, a sensor recognizing and characterizing this movement, and a connection of the sensor to some computing device, typically through the Internet.

ones, and connected via the Internet for the transfer of observed data. While these devices carry unique identifiers, in many applications their location is also critically important for the interpretation of their collected data. For example, if a sensor measures air quality, then, for a proper understanding of its reading, it is necessary to know where this reading has been taken. For a sensor set up at a fixed location in the city this location might be recorded once, at the time of set-up. But sensors embedded in mobile objects must synchronize their readings with the current location of the sensor platform. Therefore, sensors embedded in mobile objects typically are also observing the mobile object's location.

A location is always a location with respect to something else. So this location can be described only in a reference system (Chapter 2). For example, a moving vehicle has embedded sensors that track its distances from the vehicle in front or from the road markings, in order to describe its location in relationship to these other objects. That same vehicle can also carry a sensor to receive satellite signals for triangulating its position within an abstract coordinate system (or you might say, relative to the current locations of the satellites, but then the definition of a location becomes circular). And again, this vehicle can carry an RFID chip that communicates with toll bridges, capturing its location as it passes them. These three examples respectively highlight (1) a dynamic relative reference frame among other moving objects, (2) an absolute reference frame with respect to the Earth, and (3) a static relative reference frame with respect to an anchor location.

This chapter will relate to such reference frames and lay the foundations for observations in these reference frames. At the end of this chapter you should be able to distinguish categories of capturing and describing location over time, which means especially of mobile objects or individuals. You should be aware of errors that adhere to all measurement data, and sensitivities about location data. We will conclude by discussing two major applications of tracking data: travel mode detection and map matching. The framework for collecting, characterizing, and analyzing data discussed in this and the following chapters lays the foundation for *intelligent transportation systems*, or ITS. Accordingly, *intelligent transportation systems subsume all efforts to use data to improve the capacity, safety, and environmental impact of existing transport infrastructure*.

3.2 Internet of Things

The Internet of Things (IoT), defined above as sensing and computing devices that are embedded in everyday objects, including mobile ones, and connected via the internet for the transfer of observed data, relies on unique identifiers for the devices and standard protocols to communicate between these devices (ITU, 2014). The devices not only sense, but are also often coupled with mechanical and digital machines to control the physical environment. Two typical, and overlapping application domains for the Internet of Things are *smart cities* and *transport*. For these domains, the International Telecommunication Union's Study Group 20 is fully dedicated to promote interoperability in the Internet of Things.[1] Similarly, the Open Geospatial Consortium (OGC) is working on an "open, geospatial-enabled and unified way to interconnect the Internet of Things' devices, data, and applications over the Web" in what they call the SensorThings API.[2] The emerging OGC standard provides already "a standard way to manage and retrieve observations and metadata from heterogeneous IoT sensor systems".

In the context of urban mobility – the overlap between smart cities and transportation, and a prime example of a heterogeneous system – the Internet of Things provides the observations to connect:

- people to needs, including vehicles;
- vehicles to vehicles;
- vehicles to infrastructure.

In each of these categories a range of relevant applications relies increasingly on the Internet of Things technology.

3.2.1 People to Needs

Computing devices in the hands of people – their smartphones, tablets, laptops, wearables, and other connected computing devices – are typically equipped with a range of sensors, and they are connected to the Internet. These devices enable a range of applications connecting people to their needs. Applications relevant for mobility can facilitate more efficient mobility services or even reduce the demand for mobility.

A prominent category of applications that reduce the demand for mobility are those supporting work or study online. An employer working from home does not need to commute, and a school kid in an online teaching program does not

[1] `https://www.itu.int/en/ITU-T/studygroups/2017-2020/20/Pages/default.aspx`
[2] `https://www.ogc.org/standards/sensorthings` – OGC, 2015/2017

require a parent (or a bus) to bring them to school. They achieve their needs without the need to move. Behind these applications there are usually cloud-based platforms that track the identity (and for this purpose also often the location) of their users. Another category of applications is concerned with the coordination between people. Colleagues that commute together ("ride-sharing") reduce the demand for vehicles on the road; the basis for this coordination is a cloud-based platform that matches requests based on their locations and travel times. Demand-responsive public transport solutions fall into this category as well. They are based on tracking the location, occupancy, and actual travel commitments of vehicles and the location and travel demand of people in order to provide real-time matching. Even mass transport can be improved by Internet of Things technologies, for example, by tracking the occupancy of vehicles on the road and estimating people's current travel demand, or by tracking the location of vehicles on the road and estimating their arrival times (Verma et al., 2020).

3.2.2 Vehicles and Vehicles

Nowadays, vehicles carry an increasing number of sensors, most of which ensure road safety and enable autonomous driving. While autonomy, in the first instance, relies fully on decisions made by computational devices on board the a vehicle, autonomous driving can become even smarter by connecting this vehicle with other vehicles or the infrastructure. Connected autonomous vehicles (CAV) allow for greater situational awareness of the individual vehicle, supporting advanced driver assistance / advanced autonomous driving systems, for example, speed adaptation or early braking fed by greater foresight or sight around street corners. CAV also allows for cooperation (cooperative intelligent transportation systems, C-ITS), such as vehicle platooning, or cooperative parking systems. Cooperative ITS have two additional challenges compared to autonomous decision making:

- One is the *certainty* that the collaborator behaves as expected. If heterogeneous agents cooperate, communication is a basic requirement, but is susceptible to communication failures (e.g., one agent reporting velocity in mph, the other taking it for km/h). Thus, certainty is a matter of agreeing on standardized protocols and exchange languages (Zheng et al., 2015).
- The other challenge is the *trust* that the collaborator is acting in the mutual interest of all. Any system of heterogeneous agents, in principle, is susceptible to deception (e.g., by agents seeking their own advantage in traffic, or by agents with malicious intent). Trust is therefore a matter of cybersecurity and more difficult to address. Among the approaches to establish trust between agents are: looking for redundancy and assessing all evidence (Shafer, 1976; Truelove et al., 2017), or, vice versa, demanding proof of location (Amoretti et al., 2018).

At the time of writing this book, two vehicle-to-vehicle communication systems (V2V) are competing for the same frequency spectrum: the Wi-Fi based dedicated short-range communication (DSRC), and the cellular based 5G. DSRC is an open standard with a range of about 300 m, while 5G is licensed (with fees to operators) and has a slightly larger range (500 m) and shorter latency, but also a shorter shelf life and a significant reliance on infrastructure. While the development of V2V communication systems has been stalled by these two mutually incompatible systems competing worldwide, we put this debate aside and work with the principles of V2V communication.

In principle, applications using V2V communication pursue *decentralized* solutions, or solutions found between and agreed by peers (Duckham, 2013), compared to *centralized* solutions that are decreed by a central authority. An example of a decentralized application is a speed adaptation system: If vehicles share information with vehicles following them that they are about to brake, then the vehicles that are behind can use this information to adapt their speed early, and to coordinate their slowing down times with each other to achieve a smoother traffic flow. No central authority is required – as any central authority would be overwhelmed by the task of optimizing traffic flow at this level. Centralized applications rely on the sensors on board vehicles as well, which presumes other forms of vehicle communications (vehicle to infrastructure, see 3.2.3). An example for such a centralized application – one where a centralized authority provides benefits from its global overview of traffic – is an internet-enabled car navigation system that is able to reroute vehicles in case of road congestion or closures ahead. In this case, no V2V communication is required. Thus, applications using V2V communication are typically operating locally instead of globally. As a consequence they are achieving locally optimal solutions, but not globally optimal solutions: the vehicles (or drivers) operate with limited knowledge.

Since V2V communication is supporting mostly local applications, the communication can be managed to become spatially and temporally sensitive: broadcasting can be limited to certain ranges and time frames. Several communication strategies have been suggested in the literature. Flooding is the most simple one: every vehicle that receives a message instantaneously re-broadcasts the message. To limit this to local applications, flooding can be limited to a certain range or area: only vehicles that are within this range or area would rebroadcast. Other strategies have been designed to reduce the large redundancy of the flooding strategy but still cover all the vehicles in the intended area, among them, a probabilistic strategy (only a certain percentage of vehicles re-broadcast) and a distance-based strategy (only distant vehicles in the communication range re-broadcast). Also, to maintain a message over certain time frames, and inform vehicles that enter the range or area late, these strategies can be applied periodically.

In the context of this book, we are mostly interested in V2V applications that have an impact on parking pressure. These are applications that improve transport capacity such that there are fewer vehicles on the road, and applications that support cooperative parking behavior. Other applications, such as for safer or for smoother driving will be neglected.

An obvious example of such applications is cooperative parking in a large car park, where some vehicles are leaving their parking spot and others are searching for a parking spot. If a vehicle leaving the car park broadcasts the freed parking spot to vehicles nearby then the searching vehicles receiving these messages can take this information into consideration in their own search strategy. Simulations have shown that cooperative parking in such an opportunistic manner, i.e., with no booking mechanisms through a central authority, reduces the search time for vehicles (Aliedani et al., 2016; Aliedani and Loke, 2019). Since this cooperation relies on the vehicles' abilities to locate themselves (in relation to the free(d) parking spots), and these abilities are degraded in indoor environments such as parking garages, others have worked on localization in parking garages to improve cooperative parking (Balzano and Vitale, 2017).

3.2.3 Vehicles and Infrastructure

Communication technologies such as the Wi-Fi based DSRC and the cellular based 5G can also establish communication channels to base stations installed at fixed locations in the infrastructure. Strictly speaking, cellular-based 5G is bound to such base stations anyway, although, in the narrow sense of vehicle-to-infrastructure (V2I) communication the infrastructure partner is one that interacts with traffic or vehicles directly.

An example of such an interaction is a traffic light that communicates its signal phase and timing information to approaching vehicles. In response, the approaching vehicles can optimize their fuel consumption by adapting their speeds early (Rakha and Kamalanathsharma, 2011). A more advanced example considers bi-directional communication at traffic lights. This way, a smart controller in the traffic light can optimize the traffic flow based on the number of approaching vehicles from various incoming directions (Bento et al., 2012). Plenty of similar applications can be thought of. They all concern coordination bound to a location or neighborhood, such as informing about roadside or surface conditions, ephemeral events on the immediate road network neighborhood, or condition of the supporting infrastructure. One example of this is the dynamic reallocation of lanes depending on the current traffic demand: the lane direction can be quickly switched in response to a controller in the roadside infrastructure that observes traffic sensors and optimizes road use (Hausknecht et al., 2011): these instantaneous switches either need dynamic signage (for human drivers) or V2I communication (for CAV).

Parking is another example where knowledge bound to a location and an interaction via V2I is beneficial. Parking lots and parking garages are prime cases for a smart infrastructure that guides vehicles to empty (or allocated) parking spots. The occupancy of parking spaces can be observed by sensors (Chapter 10). Then, a controller in the infrastructure can take these observations and the requests from vehicles searching for a parking space and optimize the allocation of spaces (Geng and Cassandras, 2012) (Chapter 9). In this way, automated valet parking becomes feasible Löper et al. (2013); Banzhaf et al. (2017): a CAV, arriving at the valet bay of the parking garage, lets the passengers disembark, and is then guided by V2I to an allocated parking space inside the garage. When the passengers later return to the valet bay, they “call” their vehicle through an app. In order to succeed, both the vehicle and the infrastructure are not only communicating with each other (as are the passengers, through their app), but are also sensor-rich platforms: the vehicle, for its autonomous driving, and the garage, for observing the occupancy of its parking spaces. A first trial has been demonstrated successfully in a parking garage in Stuttgart in 2019.

3.3 Tracking by Sensors

A large variety of sensors are applied to track what moves in urban spaces. One dimensional barcodes and two-dimensional QR codes are applied mostly to track parcels and goods in urban logistics. Both of these are identifiers. Their location is typically determined by stationary scanners. Using this method, parcels can be checked in at certain stages of their journey. But localization also works in reverse: If the QR code is mounted at a fixed (known) location, then a mobile scanner’s location can be determined. For example, security personnel on their inspection rounds can check in at fixed locations, documenting their presence at particular times.

Radio-frequency identification (RFID) technology applies a similar philosophy but since it is radio-driven it does not need line-of-sight with a reader. RFID identification tags use electromagnetic fields to automatically identify and thus, track objects. RFID technology is used in contactless credit cards (where the location of the pay station is recorded) or in contactless smart public transport cards (where the location of the reader is recorded, and the fare is typically determined). Similarly, electronic toll collection works with active RFID readers: A vehicle equipped with an RFID tag passing the stationary reader is registered with its location and time.

Social media have become a prominent source of tracking users. Although Twitter had turned off (optional) precise georeferencing of messages in June 2019, it still allows usage of references to coarse and nearby places. Other social media, such as Foursquare, offers their users to check-in to places and share this location within their network. The distinction between ‘location’ and ‘place’ is important though. We use *location* so far as a representation of a position in a spatial reference frame (in the form of coordinates), typically derived by some measurements, such as satellite positioning. And we use *place* here for common language references, typically names of places, names of businesses at places, or postal addresses, which would need to be translated into coordinates in a spatial reference frame by a process called georeferencing.

Vision sensors, prominently among them, CCTV cameras, are also applied in urban tracking. Some applications settle for counting moving objects (pedestrians, cars) at particular locations. An example is the City of Melbourne's (Australia) pedestrian counting system, which provides open data[3]. Other applications track moving objects in scenes in order to determine flow or density parameters (Wang et al., 2014). Yet other applications aim at identifying individuals. Identification of vehicles is often done through number plate recognition, and identification of pedestrians through face recognition (Parkhi et al., 2015).

Wi-Fi networks can be used to track connected devices in two ways: by *passive* and by *active* tracking. In passive tracking (or device positioning) the smartphone listens, on each channel, for Wi-Fi access points around, including their individual signal strength, and triangulates between these access points. In active tracking (or network positioning), the smartphones' regular probe requests, which include their MAC address, are registered by the Wi-Fi access points. In this way, the network can track a device, which can then be used for movement analysis (Ruiz-Ruiz et al., 2014). Other radio-based positioning technologies work similarly in principle, such as Bluetooth, Ultra-Wide Band (UWB), and GSM (3G, 4G, 5G).

Another radio-based tracking method, however, uses only one-directional communication: the Global Navigation Satellite Systems, or GNSS (see Chapter 2). These systems rely on triangulation methods based on satellite signals. Receivers for satellite signals come in many shapes; prominent to urban mobility are trackers (GNSS tracking device and SIM card, attached to a moving object) and smartphones. The receivers used in urban mobility are relatively cheaper and have inaccurate antennas, such that, for example, autonomously driven cars cannot rely only on GNSS for their localization. But for the purposes of tracking movements, traffic, and route planning this accuracy is sufficient. GNSS belongs to a category of passive tracking methods since the positioning happens on board the mobile sensor platform (e.g., smartphone). Navigation systems on board vehicles, working with off-line maps, can access those GNSS localizations directly. But many other uses of the tracking data, including online navigation systems, require the integration of localizations of many moving agents (people or vehicles) in real-time, and in these cases, the locally produced tracking data has to be shared with a platform via a mobile internet. Other uses for tracking data are fleet management, car insurance, electronic logbooks, live alerts (speeding, servicing, area violations), or automatic emergency calls.

[3] `http://www.pedestrian.melbourne.vic.gov.au/`

3.4 Tracking Data Reference Frames

Moving objects can be observed theoretically in two ways: from a stationary viewpoint as the objects pass by, or from an accompanying viewpoint (Laube, 2014; Both et al., 2012). This categorization is borrowed from fluid dynamics, where the two viewpoints have been labelled the Lagrangian and the Eulerian frames of reference (Hirt et al., 1974; Bennett, 2006). The sensors discussed above fall in one or the other category, and thus, these two concepts will help us to categorize and better understand the observations in urban traffic management, including parking.

3.4.1 Lagrangian Frame of Reference

In the Lagrangian frame of reference, the observer follows an individual particle (in a fluid) as it moves through space and time. Consider now the particle being an object in urban traffic. Then the Lagrangian observer would follow this object and record its locations over time. The result is a *trajectory*.

Lagrangian observations are typically discrete, i.e., taken at certain points in time, but those observations should be frequent enough to reconstruct the continuous movement (x, y, t) for any t. If this frequency is lacking, the reconstruction becomes ambiguous with regard to (x, y). This discussion on frequency and ambiguity is relevant in the context of map matching, which is the reconstruction of a movement along a transport network on a map. In order to avoid ambiguity, observations are often made at regular intervals (e.g., GNSS recordings of a smartphone every 5 seconds) or in adaptive sampling rates (e.g., GNSS records only if the smartphone has been moved).

3.4.2 Eulerian Frame of Reference

In the Eulerian frame of reference, the observer focuses on specific locations in space through which a particle (in a fluid) passes. Consider again, the particle being an object in urban traffic. Then the Eulerian observer will register the passing of this object at a particular location. Tracking the number of vehicles crossing an intersection, automatic toll collection, or a pedestrian counting system are examples of Eulerian observations.

Eulerian observations, since they are taken at fixed checkpoints, are typically made by sensors installed in the environment, such as beam counters, smart card terminals, RFID readers, CCTV cameras, or the vehicle counting sensors in traffic control systems (e.g., the induction loops of SCATS, `https://www.scats.com.au/`). These sensors observe continuously.

3.4.3 Eulerian-Lagrangian Transformations

Often observations exist in one reference frame, but interpretations are sought in another reference frame. In this situation transformations between the two reference frames are required (Hirt et al., 1974; Wang et al., 2016). Chapter 2 has already introduced coordinate transformations between two coordinate reference systems but here we extend this conversion to transformations of observations in Eulerian and Lagrangian frames of reference.

Eulerian to Lagrangian transformations require recombining trajectories from traffic counts or flow data. Since elementary information about identity has been lost in the counts in a Eulerian reference frame, this transformation can only come up with an estimation of likely or representative trajectories. For example, a shopping mall that wishes to guide movement by popular routes. Tracking individuals may be infeasible due to privacy concerns (or privacy legislation), but the shopping mall operator can count the flows from one sub-area to another, for example, by installing beam counters. The density of traffic at particular beam counters can be reconstructed to identify popular routes.

Vice versa, Lagrangian to Eulerian transformations require transforming trajectories into count data. For example, a road authority may have access to household travel survey data: data where a representative sample of the population provides information of their daily travel routines. This data is Lagrangian in nature. But the road authority might be interested in investigating the traffic load at specific intersections, and therefore, converts the Lagrangian data into Eulerian data. A routine way of doing this is using a traffic simulator.

3.5 Properties of Data

The tracking data collected by any technology shows a range of properties that have been specified as data quality components (Veregin, 2005). Here we discuss uncertainty, currency, and frequency.

3.5.1 Uncertainty

Measurements can never be exact. This is the reason why measurements are usually repeated. Repeated measurements allow subsequent statistical post-processing to balance out random errors (Figure 3.2 left), and also to identify and filter out outliers. However, uncalibrated instruments can also produce biased measurements where the mean is no longer a good estimate of the true value (Figure 3.2 right). Measurements with only random errors are called accurate, while measurements with low variance are called precise. Note that, in line with Figure 3.2 on the right, precise measurements can be inaccurate.

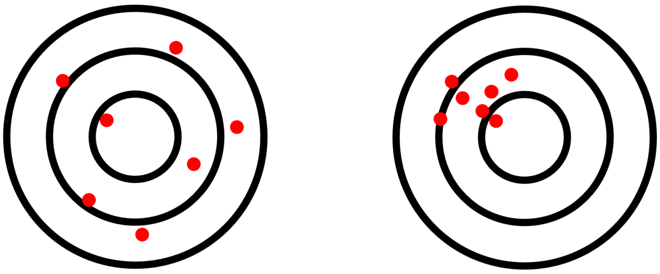

Figure 3.2: Measurements can never be exact. On the left, more accurate but less precise measurements, on the right less accurate but more precise measurements.

Take, for example, the capacity of a smartphone to position itself under the open sky, using the signals from the GNSS. A smartphone's GNSS antenna takes a large number of uncertain observations (after all, smartphones use cheap chips) and averages out the random errors. How accurate the result is, i.e., how close the result is to the true location of the smartphone, depends on the impact of systematic errors, such as currently weaker configurations of satellite positions, or multipath effects in urban canyons. Systematic errors cannot be detected from observations alone, and thus, statistical measures such as the standard deviation of repeated observations only describe the precision of a measurement, but not its accuracy. Accordingly, avoiding or controlling systematic errors is critical for measurements, because only then is the most prominent statistical measure, the *mean*, close to the true value. Your favorite mapping app shows a blue circle, centered on the mean, and of a size describing the precision of the measurement. Since mapping apps are commercial services, they are not too transparent about the meaning of these circles, but it is likely that they are linked to some confidence interval, which would be computed from the standard deviation.

3.5.2 Data Currency

Many applications of intelligent transportation systems, such as vehicle control, depend on real-time data. However, since communication channels are involved between the observation itself (the sensor), the analysis of the observation (e.g., a cloud-based service), and the use of the derived information (e.g., by a vehicle, or by a driver), real-time operations can only be realized with some latency. In the above example of a mapping app, if the sight to satellites is lost for a while – for example, because a pedestrian walks under dense tree foliage, or a car drives through a tunnel – the smartphone can only show the last known position, which over time gets more and more out-of-date. Hence, data currency has to be actively tracked and considered in the design of applications.

3.5.3 Frequency

Many observations in intelligent transportation systems are not made continuously, but with regular or irregular frequency, or the sampling rate. For example, smartphone navigation apps sample the position of a smartphone every couple of seconds – the exact intervals may adapt to current speed and travel mode. A public transport smartcard tracks a person's movement only with check-in and check-out. Frequency has an impact on the interpretation of observations. If, for example, a car's location is known every ten minutes, the route it has traveled can be reconstructed only with some ambiguity. Accordingly, frequency is considered as another data quality component.

3.6 Privacy Implications of Transport Data

Politico titled a story in 2018: "Google is building a City of the Future in Toronto. Would Anyone Want to Live There?" The story refers to Sidewalk Labs' (Alphabet's smart city arm) of Toronto's eastern waterfront redevelopment, which is based on free and fast Wi-Fi in order to track everything that moves and their activities. From a service provisioning perspective, developments like the one above, or LinkNYC's Hudson Yard redevelopment, open new opportunities for intelligent mobility. Resistance in the population, on the other hand, comes from the potential secondary use of the data, and hence lack of trust. The jury is out on whether these developments move towards smart cities or surveillance cities.

In principle, societies – always trailing behind technological developments – have to develop legal licensing frameworks and social licensing frameworks for the use of data that impacts privacy. Legal frameworks protect the fundamental values and ethical norms of a society, and are, thus, required to protect the weaker party, or the vulnerable members of the community. It does not help that data has become global while legal frameworks are still formed at national levels. Legal frameworks can demand of making data anonymous before reuse. Anonymous data, however, has also been shown to be susceptible to reidentification (Culnane et al., 2019), such that stronger regulations are needed. Social licenses, in contrast, are licenses given by individuals on the use of their data (Carter et al., 2015). Social licenses imply, first, that the individual is – legally and technically – the owner of their own data, i.e., can control its use. Then the individual might give selective permissions (consent) for uses of their data proposed by a data custodian. This consent of the owner for producing intelligent (transport) services has also been called co-creation.

3.7 Trips, Segmentation, and Map Matching

Motorized forms of mobility in the city always require some multi-modality. A person has to at least walk to a (private or public) vehicle, and from the vehicle to their destination. Further mixes are possible, for example, a person taking public transport may transfer between vehicles or modes. In urban transportation we call a movement between two stationary activities a *trip* (Das and Winter, 2016). Hence, a trip consists of a sequence of movements in specific travel modes that are taken with no intended interruption for a planned activity, i.e., including wait times. Correspondingly, a day can be partitioned into *trips* and *activities* between these trips.

Trips and activities between these trips are also the common units of household integrated travel and activity surveys (Roddis et al., 2019; Stopher et al., 2007). The survey data is rather abstract – a typical entry would be, for a member of a household: "7:00 a.m.–7:30 a.m. travel from home to work". Trajectory data from intelligent transportation systems can provide more details about this trip (Carrion et al., 2014), by splitting the trip into individual segments, for example, by travel modes, and breaks, including wait times. This process of travel mode detection produces segments (of single modes) by some common properties in the trajectory. As it is based on actual trajectory data, it typically provides more accurate data than the surveys themselves (Bricka and Bhat, 2006; Zhao et al., 2015). For example, the trip above could be captured by high-frequency GNSS and inertial sensor observations on a participant's smartphone and then interpreted by segments of "7:02 a.m.–7:11 a.m. walking; 7:11 a.m.–7:13 a.m. stationary near/at a bus stop (waiting); 7:13 a.m.–7:24 a.m. on a bus on Line 76; 7:24 a.m.–7:26 a.m. walking". An integration of this data with public transport real-time tracking data could additionally reveal the specific bus or vehicle, which, according to smartcard data interpretation, was crowded at that time. Further refinements are possible, although not often needed in intelligent transportation systems. For example, the waiting time may have involved some wandering around to cope with the cold weather. The segmentation process is also, in principle, a hierarchical one, since each segment can be split into further segments in more detail. For example, embarking a bus – switching travel mode from walking to riding on a bus – does not happen in an instant, but could be split into queuing, embarking, ticketing, and walking to a seat (Das and Winter, 2016).

3.7.1 Mode Detection

Partitioning and labelling the segments of a trip by travel mode are often the first steps of semantic trajectory analysis, which in general aims to attach meaning to connected sequences of (x, y, t) triplets forming a trajectory (Parent et al., 2013). To identify a segment of a particular travel mode commonly high-frequency GNSS observations on a traveler's smartphone are available (sequences of (x, y, t)). Additional inertial sensor observations or compass measurements enrich the interpretation process and reduce its uncertainty.

Mode detection can be divided into the steps of detecting discontinuities in the trajectory (indicating modal change), and then labelling the segments by travel modes or activities. According to this order of processing, real-time mode detection is more challenging because of the real-time detection of a discontinuity.

The labelling of a segment can be formulated analytically. For example, a fuzzy set classification method uses rules such as "if the movement along a segment between two stops is never going faster than 5 kilometers per hour, and generally located on sidewalks, then this is walking" (Das and Winter, 2018). Other mode detection methods leave it to (deep) machine learning to detect travel modes from trajectory characteristics (Soares et al., 2019; Nikolic and Bierlaire, 2017). Explicit characteristics are usually as below:

- the speed of traveling, although speed alone is ambiguous in urban mobility;
- stop locations, e.g., at traffic lights or at bus stops;
- acceleration patterns, distinguishing, for example, a heavy vehicle from a light vehicle;
- noise patterns, e.g., of a private car, a bicycle, or a bus;
- space traveled through, e.g., road space, sidewalks, pedestrian zones, or light rail tracks;
- public transport schedules, and ideally real-time tracking data of public transport vehicles to compensate for deviations from the schedule;
- and land use at the start and end of the segment in order to estimate activities.

Mode detection algorithms are challenged by measurement uncertainties. Positioning uncertainty alone has an impact on (a) detecting stationary activities (while the observations are showing random movement), (b) first and second derivatives from positions (x, y, t), i.e., speed and acceleration, which are more sensitive to positional uncertainty when the GNSS observation frequency is higher, and (c) the spatial separation between networks (e.g., where tracks go next to road lanes).

3.7.2 Map Matching

Closely related to mode detection is the challenge of map matching. Map matching addresses the uncertainty in the trajectory data not for estimating the travel

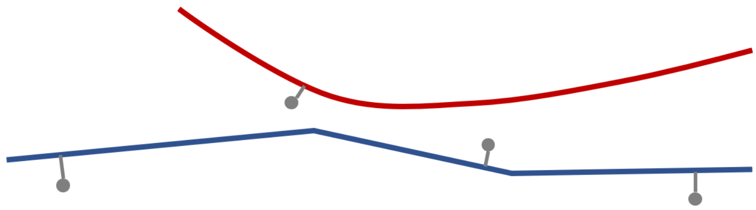

Figure 3.3: Map matching of the uncertain GNSS positions along a travel route often goes wrong when you are simply looking for the next road center line.

mode, but for estimating the most likely position of a tracked moving object on the mode's network. The conundrum is that map matching seems to require mode detection being solved first, in order to pick the most appropriate modal travel network. But mode detection itself is based on estimating the space (or network) traveled through already. This conundrum is usually circumvented in the literature by assuming that the travel mode is known. For example, a car navigation system's trajectory is a trajectory of a private vehicle, and thus a trajectory of a movement along a public road network. For these more trivial cases, a large number of map matching algorithms has been proposed, among them (Newson and Krumm, 2009; Quddus et al., 2009; White et al., 2000; Brakatsoulas et al., 2005). If the travel mode is known to change along the trajectory, only combined approaches lead to meaningful results. But if the travel mode is not known, both travel mode and map matching have to be estimated at the same time.

Map matching matches the measured positions, which are afflicted with uncertainty, with their most likely positions on the modal network, in order to infer the tracked object's actual path. In principle, if the object is a road vehicle, and the modal network the road network, one might want to match an observation (x, y) to the nearest road's or lane's center line. But just matching position to the nearest center line is prone to errors, as the sequence of the identified center lines may not lead to a realistic path (Figure 3.3). Hence, map matching requires methods that consider also the likelihood of the identified center lines within the logic of a travel journey.

One method containing this strategy is the hidden Markov model, HMM, a statistical model of a Markov process (Newson and Krumm, 2009). A Markov process is a sequence of events where the probability of each event depends only on the state attained in the previous event. For a trajectory in a map matching process, we can focus on the last "map matched" (visited) location and the next observed location to estimate the next visited location (Figure 3.4 left), which is sufficient to construct a realistic path for a trip segment. For the application of a Hidden Markov Model, first, all of the candidates for next locations are computed, which are all the nearest map matches for an observation within a reasonable range (Figure 3.4 center). Finally, the transition probabilities from the last visited location to all the possible next locations are computed, such that the sum of

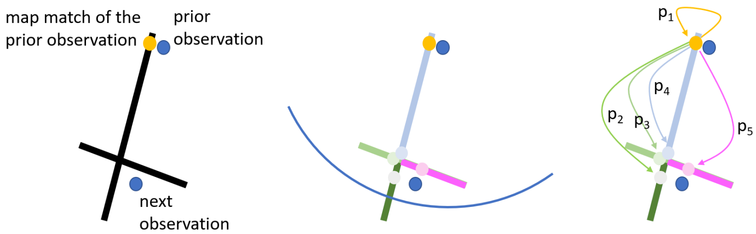

Figure 3.4: The Hidden Markov Model applied to map matching.

all these probabilities equals 1. This transition probability is, in its simplest case, just a function of the difference between the observed distance (between the blue points in Figure 3.4) and the traveled path distance (between the yellow point in Figure 3.4 and the potential next locations). But this function can be made more complex in order to consider more contextual information in what is a reasonable path. For example, it can consider inertial sensor or compass observations in addition to location, the actual speed of the vehicle, and the road speed limits, as well as the travel patterns of the driver.

Map matching relies on reasonable sampling rates. When sampling rates are too low, many travel options exist prior to the next observed location, and the matching process becomes indeterminate. When sampling rates are too high, the distances measured become very different from the distance traveled, due to uncertainty in the measurement.

3.8 Conclusion

Location data is increasingly becoming available from sensors integrated in urban mobility. This chapter has introduced some tracking technologies and their properties, and then defined the notion of a trajectory with its critical properties of frequency (sampling rates) and accuracy (linked to map matching). Intelligent transportation systems rely on tracking data from everything that moves (Zhu et al., 2019; Guerrero-Ibáñez et al., 2018).

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