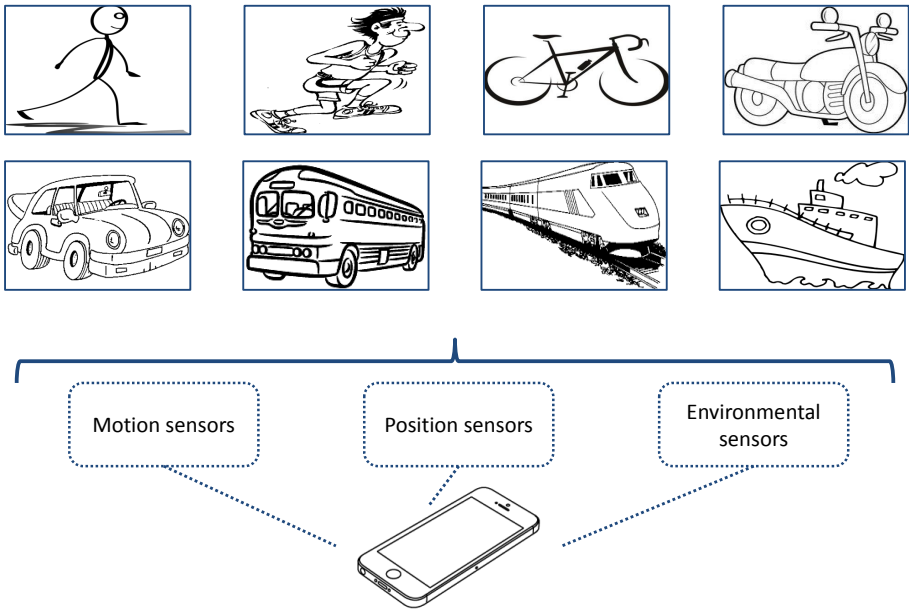

Review of transportation mode detection approaches based on smartphone data

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Transport and Mobility Laboratory, EPFL **May 2017**

STRC | **17th Swiss Transport Research Conference**
Monte Verità / Ascona, May 17 – 19, 2017

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May 2017

Abstract

The usage of smartphones has rapidly increased during the last years. In addition to communication capabilities, they are also equipped with several sensors, and are usually carried by people throughout the day. The data collected by the means of modern smartphones (e.g. location based, GSM, and other contextual data) are thus valuable source of information for transportation analysis. In this paper we focus on smartphone data used for transportation mode detection. This is important for many applications including urban planning, context related advertisements or supply planning by public transportation entities. We present a review of the existing approaches for transportation mode detection, and compare them in terms of (i) the type and the number of used input data, (ii) the considered transportation mode categories and (iii) the algorithm used for the classification task. We consider these aspects as the most relevant when evaluating the performance of the analyzed approaches. Finally, the paper identifies the gaps in the field and determines future research directions.

Keywords

travel mode, classification, smartphone sensors, machine learning

1 Introduction

Smartphone penetration in developed countries is currently over 70% among adults, and the number of smartphone users is forecast to grow from 1.5 billion in 2014 to around 2.5 billion in 2019 (Statista, 2017). Technology improvements in smartphones have brought incremental enhancements. Modern smartphones are more than just calling devices. The capabilities of a smartphone also include the ability to send or receive emails, view documents, access the Internet, send or receive multimedia messages, use GPS, other useful features such as different applications and games. They are also equipped with various sensors that measure motion, orientation and environmental conditions. Using the capabilities provided by smartphones, it is now possible to capture information that was considered to be beyond our reach. Because smartphones are almost always with their users, they know where the users are, how much time they spend in certain places, what they are interested in, what they like, and how they feel. Many of these capabilities do not rely on the user reporting. Instead they work passively when collecting useful data.

The use of smartphones is not anymore limited to the traditional telecommunication field only. It extends to applications in other fields. For instance, the explosive spread of smartphones has provided the transportation field with a new potential. In this field, transportation activity surveys were typically used to collect information for urban transportation planning. These surveys are conducted through conventional questionnaires and travel diaries to investigate when, where and how people travel in urban areas. The data collected by the means of modern smartphones have a potential to solve most of the shortcomings associated with conventional travel survey methods, including biased response, no response or erroneous time recording. Smartphone data is also utilized for discovering places of interest (Montoliu *et al.,* 2013) and visiting patterns (Do and Gatica-Perez, 2014), capturing the daily transportation activity profiles of users (Cottrill *et al.,* 2013), inferring activity sequences (Danalet, 2015), modeling route choice behavior (Bierlaire *et al.,* 2010, Kazagli *et al.,* 2014), estimating driving behavior (Eren *et al.,* 2012), etc. Using smartphones as a survey tool also brings certain challenges. They are related to battery life and a large variety in terms of operating systems, brands and types.

In this paper we focus on smartphone data used for transportation mode detection. It is important for many applications, including transportation studies, urban planning, health monitoring, computer supported elder-care, epidemiology, etc. With the knowledge of travelers' transportation mode, targeted and customized advertisements may be sent to their devices. This information is also useful for the development of context aware cell phones that sense the current context and adapt their behavior accordingly. Also, if the precise transportation modes of individual users are discovered, it is possible to provide a more realistic picture of travel demand. This

knowledge may help to determine the environmental impact of travel patterns, such as carbon footprints of users, and track the daily step count of users and amount of calories they burn. Another application is the detection of real-time traffic state, because companies such as Google collect data from mobile phones in order to estimate the traffic speed on roads.

The structure of the paper is as follows. Section 2 describes main characteristics of the approaches proposed for transportation mode detection. The type of used input data, the considered transportation mode categories and the algorithms used for the classification task are discussed. In Section 3, several approaches proposed in the literature are described and evaluated in terms of their performance. Finally, in Section 4 several open challenges are discussed as well as possible ways to extend the capabilities of current approaches.

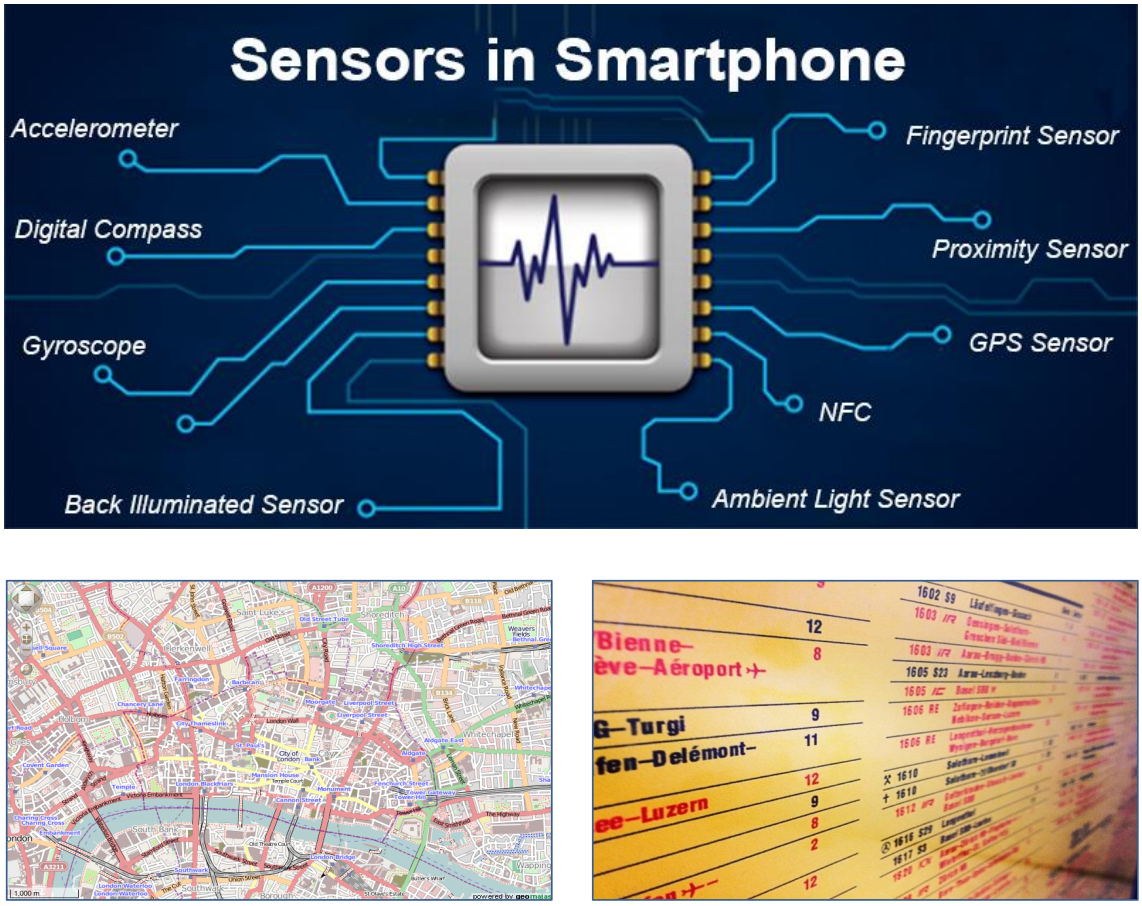
2 Characteristics of the approaches

In this section, we discuss main characteristics of the approaches proposed for transportation mode detection. They include data sources and corresponding features, algorithms and transportation mode categories considered in different approaches. In therms of the methodology, the approaches are rather similar. First, suitable features are extracted from the raw sensor data, then a training dataset is used to train an algorithm, and finally the algorithm is used to predict unseen data based on the heuristics learned during the training phase. In the following, these aspects are elaborated in details.

2.1 Data sources

To determine the mode of transportation based on smartphones, the data from different built-in smartphone sensors can be used. Most modern smartphone devices have sensors that measure motion, orientation, and various environmental conditions. They are capable of providing data with high precision and accuracy. These sensors are useful for monitoring three-dimensional device movement or positioning, or for monitoring changes in the ambient environment near a device. Motion sensors include accelerometers, gravity sensors, gyroscopes, and rotational vector sensors. Position sensors include orientation sensors and magnetometers. Environmental sensors include barometers, photometers, and thermometers. In addition to mobile device sensor information, some external data source can also be valuable. We give next an overview of the smartphone sensors and external data sources typically employed in transportation studies (Fig. 1).

Figure 1: Data sources for transportation mode detection



Accelerometers are able to measure the physical motion of a solid object. That is, they measure the acceleration force that is applied to a device on all three physical axes, including the force of gravity. Accelerometers are primarily used for orientation sensing in smartphones. Transportation studies have suggested that the acceleration generated during human movement varies across the body and depends upon the activity being performed (Hoseini-Tabatabaei *et al.,* 2013). The key feature that makes this sensor attractive is low energy consumption.

Gyroscope measures a device's rate of rotation around each of the three physical axes. It can provide orientation information, and provides an additional dimension to the information supplied by the accelerometer. Gyroscopes are characterized by low power consumption, but are prone to error accumulation as a result of significant calibration errors, electronic noise and temperature (Woodman, 2007).

Magnetometer measures the ambient geomagnetic field for all three physical axes. It provides mobile phones with a simple orientation in relation to the Earth's magnetic field.

Global Positioning System (GPS) sensor provides the position and velocity of the user that is measured based upon the distance of the mobile phone and each of a number of satellites in two dimensions (Ajay, 2004). Connection to three satellites is required for two-dimensional positioning, and the precision increases with more visible satellites. GPS does not work indoors, and is therefore primarily used for outdoor positioning. Also, it is characterized by reduced precision of positioning in dense urban environments, due to the fact that buildings reflect and occlude satellite signals. GPS is considered as the most power consuming localization technique for mobile computing, and it reduces the battery life of the phone significantly. The accuracy of this system is between 50 to 80 meters and can be improved to an accuracy of up to 10 meters (Kyriazakos and Karetsos, 2000).

Cellular network signals are used by the phone for calls and data transfer. The most widespread cellular telephony standard in the world is Global System for Mobile Communication (GSM) (Mun *et al.,* 2008). A GSM base station is typically equipped with a number of directional antennas that define sectors of coverage or cells. A cell is therefore a geographic region within which mobile devices can communicate with a particular base station. Each cell has a unique cell identifier. The fluctuation pattern of cell identifiers together with signal strength can provide information on the position of a phone. To collect this type of data, an application that measures and records the surrounding radio environment has to be installed on a mobile device (Sohn *et al.,* 2006). Mobile phones can be tracked in outdoor and indoor contexts. A precision varies depending on cell size from 50 to 200 meters, but can deteriorate even more in low density areas (Liu *et al.,* 2007). Cellular network signals are associated with "ping-pong" phenomenon, which appears when a user is within the coverage of two or more stations. Signal strength from the stations fluctuates and causes repetitive changes of associated cell even when users are stationary. Researchers have also analyzed the data from mobile phone operators (Calabrese *et al.,* 2011, Gonzalez *et al.,* 2008, Onnela *et al.,* 2007) consisting of anonymous location measurements generated each time a device connects to the cellular network (e.g. when a call is placed or received, when a short message is sent or received, when the user connects to the Internet, etc.). However, these measurements are available only during the time that the device is in use, or when the associated cell changes over time (e.g. during a trip).

Bluetooth allows wireless connectivity and short range communication. Bluetooth sensors are able to sense devices in their vicinity, and to obtain their Bluetooth identifiers, names and types. The range of Bluetooth scanners and penetration rate vary between 10 to 100 meters, respectively between 7% and 11% (Versichele *et al.,* 2012).

WiFi provides wireless connectivity to devices inside a Wireless Local Area Network (WLAN). The WLAN provides communication ranges of up to 100 meters and allows to track devices outdoor and indoor (Hoseini-Tabatabaei *et al.,* 2013). Smartphones do not need to be logged

on to the WLAN, but their WiFi antennas has to be turned on. The positioning accuracy is low. It is possible to improve the localization in case when there are more than one access point available using for instance signal triangulation and fingerprinting (Danalet, 2015). WiFi is the most power-demanding sensor after GPS when used to provide location information. The effect called "ping-pong" is also typical for WiFi data.

Other sensors include *barometers* that measure atmospheric pressure and can be used to detect how high the phone is above sea level, *thermometers* and *humidity sensors* that measure ambient temperature and air humidity, *cameras*, *microphones*, etc.

External data sources can provide additional useful information in transportation studies. They include network infrastructure data and route maps, as well as the time schedules of public transportation modes in a static or a real-time form (OpenStreetMap, 2017, geOps, 2016).

2.2 Feature extraction

Raw data collected by different smartphone sensors is typically transformed into more computationally efficient and lower dimensional sets of features. The extracted features are intended to be informative and relevant for the learning task. A variety of feature-extraction techniques are used in the literature, based on different mathematical and statistical procedures. The raw sensor data is usually segmented into several windows and features are extracted from a window of samples. The window size, as well as the sampling frequency, are important parameters, as they both affect computation and power consumption of sensing algorithms. Smaller window sizes cause classification accuracy to suffer due to certain features not being effective (e.g. accelerometer frequencies) and larger window sizes may introduce noise in the data.

Time domain and frequency domain features are commonly used for transportation mode detection tasks. Time domain features are used to characterize the information within the time varying signal (Biancat *et al.,* 2014). Many studies use raw speed or acceleration data, and GPS positioning information over time as input features. The difference in distance covered between measurements and heading changes are used in addition. For accelerometer signals, the features such as mean, standard deviation, median, minimum or maximum of the signal are the most commonly used in time domain. GSM signal strength and cell tower fluctuations are utilized for inferring different states of user motion.

Frequency domain features are regarded as more computationally demanding compared to the time domain features. This is due to an additional processing step, related to the data transformation from the time to the frequency domain. An example of these features, the peak

frequency of the power spectral density of the accelerometer signal, is reported in Ermes *et al.* (2008).

Features extracted based on external data typically include bus location closeness, bus stop closeness and rail line closeness (Stenneth *et al.,* 2011).

2.3 Algorithms

The algorithms used for transportation mode detection can be categorized as discriminative or generative (Fig. 2). Generative algorithms model class-conditional probability density functions and prior probabilities. As such, they allow to generate samples from the derived joint distributions, and are typically flexible in expressing dependencies in complex learning tasks. Popular algorithms from this group include Naïve Bayes, Bayesian Networks, Mixture Models and Hidden Markov Models.

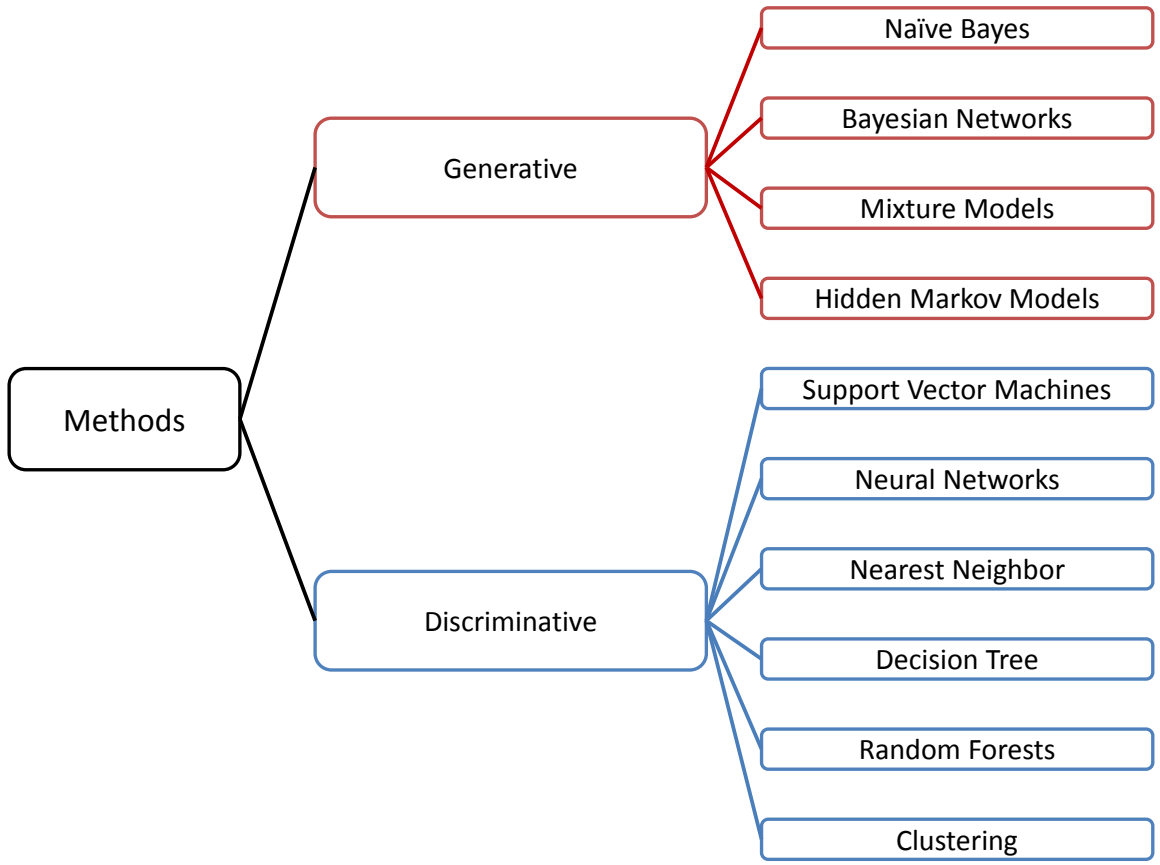
Discriminative algorithms do not attempt to model underlying probability distributions. Instead, they are focused on a direct estimation of posterior probabilities. Popular discriminative algorithms include Support Vector Machines, Neural Networks, Nearest Neighbor, Decision Tree, Random Forests, Clustering, etc. For more details on the algorithms, we refer to Bishop (2006).

2.4 Transportation mode categories

Different studies reported in the field have proposed different categorization of transportation modes. Transportation modes can be roughly classified into motorized and non-motorized, or soft modes (Fig. 3). Motorized modes include cars, motorcycles, trucks, buses, trams, metros and trains. Walking, running and biking are typical representatives of soft modes. Soft modes contribute to the reduction of congestion and pollution, the enrichment of the local environment, the improvement of quality of life, enhanced accessibility and social equity. One strategic objective in many European countries is therefore the promotion of soft modes, which together with public transport represents an energy-efficient and low resource-consuming means of transport (Oja and Vuori, 2000).

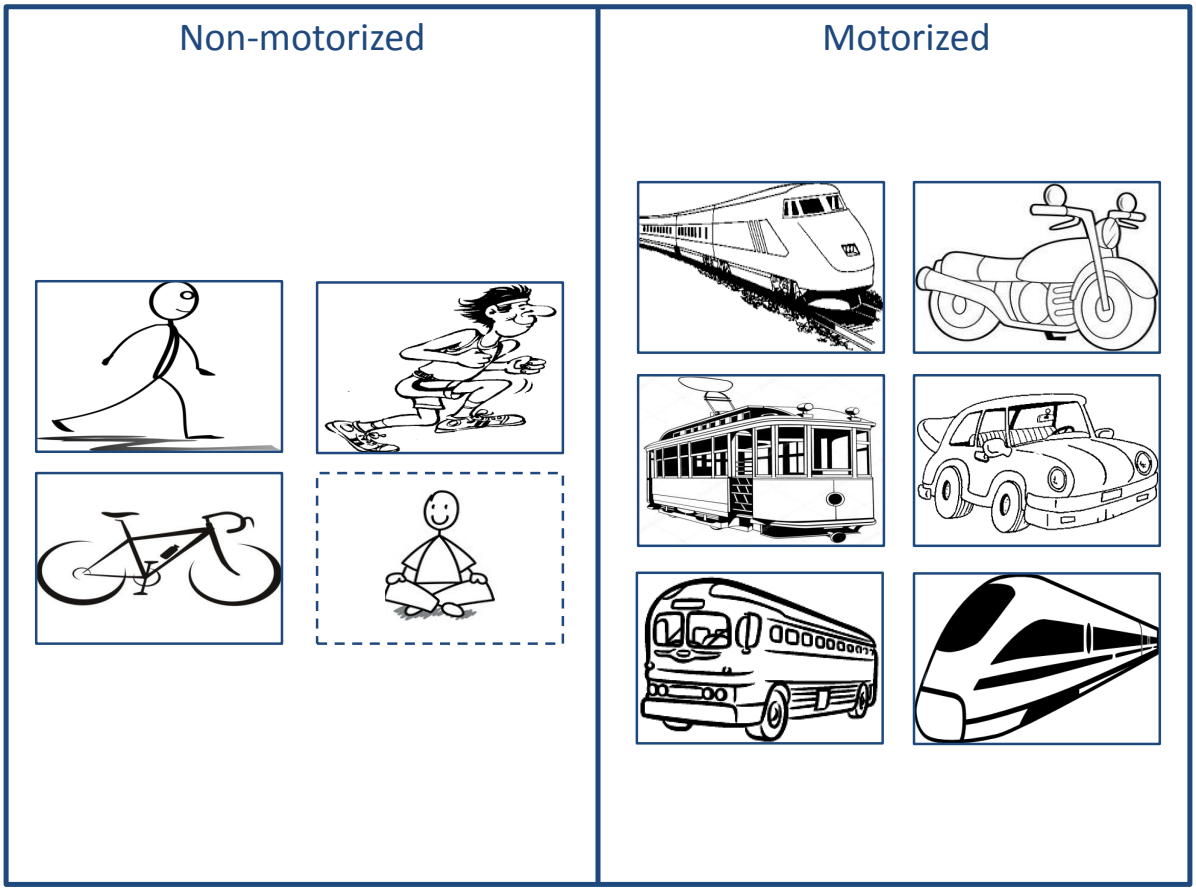
Intuitively, different transportation modes have different mobility patterns. For instance, motorized modes generally have a higher speed than soft modes. Fig. 4 shows the normalized histograms of the recorded speed data and the estimated speed distributions for five modes, as reported in Chen and Bierlaire (2015). Walking and biking can be in general successfully

Figure 2: Methods used for transportation mode detection



differentiated from other modes. However, slow walking can be rather similar to no movement, and biking can be very similar to the cars. As for the latter, the similarities are reflected through similar speeds and routes of bikes and cars in the cities and absence of fixed schedules. Buses are supposed to follow fixed routes and schedules, which places them apart from the categories above. However, due to high volumes of traffic, significant discrepancies may occur making buses one of the categories that are more difficult to predict. Trams, metros and trains follow routes and schedules like buses, but are not subject of delays induced by traffic congestion. Their routes may contain underground parts, causing poor quality or non-existence of certain smartphone signals. Many studies additionally consider stationary mode, which refers to a not moving state of an object, and as such significantly differs from other categories.

Figure 3: Transportation mode categories considered in the literature



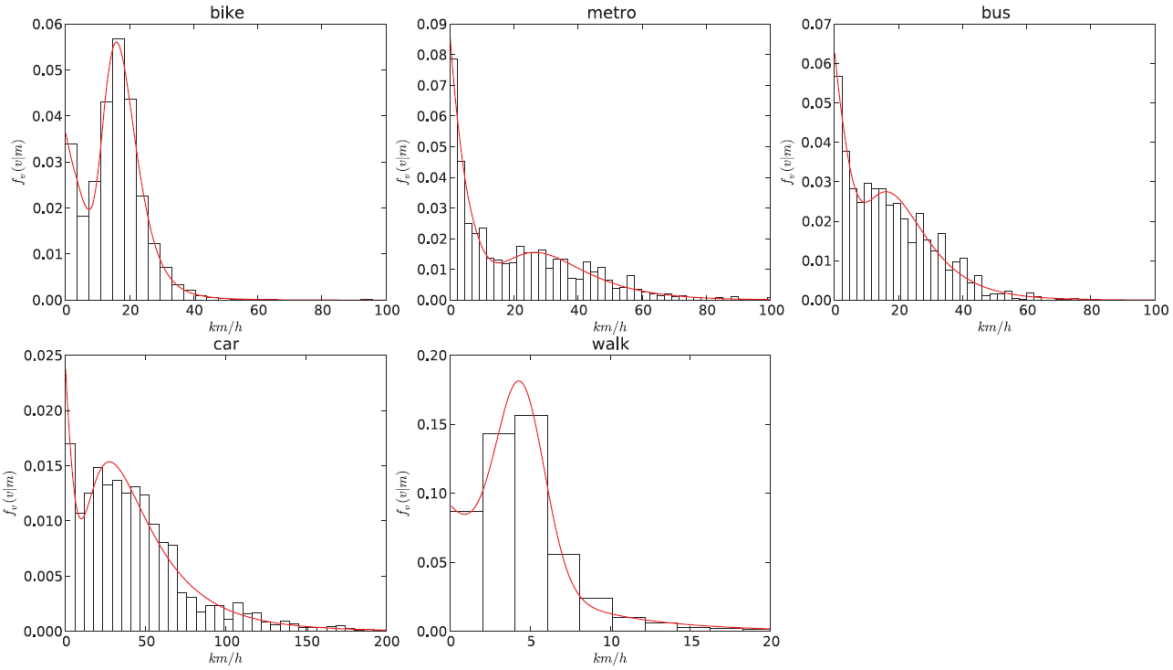
3 State of the art

This section discusses several approaches for transportation mode detection proposed in the literature. First, we give a general description of the approaches. Then, a comparison of the methods and their performances are reported.

3.1 Description

Patterson *et al.* (2003) present an unsupervised method of learning a Bayesian model from a GPS sensor stream. The approach simultaneously learns a unified model of the traveler's current mode of transportation and her most likely route. Car, bus and walking are considered transportation mode categories. It is also demonstrated that the accuracy of the approach is improved by adding more external GIS knowledge.

Figure 4: Speed distributions of five transport modes



Source: Chen and Bierlaire (2015)

Muller (2006) demonstrate that by using the patterns of GSM signal strength fluctuations and changes to the current serving cell and monitored neighboring cells it is possible to distinguish between various states of movement such as walking, driving in a motor car and remaining stationary. They present a Hidden Markov Model for inferring the current activity of the cell phone carrier.

Sohn *et al.* (2006) explores how coarse-grained GSM data from mobile phones can be used to recognize high-level properties of user mobility. The proposed approach is a two-stage classification scheme. The first stage classifies an instance as stationary or not. If the instance was classified as not stationary, a second classifier would determine if the instance was walking or driving. Both classifiers are trained using a boosted logistic regression technique. The algorithm is able to distinguish if a person is walking, driving, or remaining at one place. In the experiments the authors have also shown the superiority of the proposed two-stage classification compared to Naïve Bayes, Support Vector Machines, and heuristic-based methods.

Reddy *et al.* (2008) focus on the transportation mode of an individual based on GPS and accelerometer smartphone data. The goal is to determine whether an individual is stationary, walking, running, biking, or uses motorized transport. The proposed classification system consists of a decision tree followed by a first-order Hidden Markov Model.

Mun *et al.* (2008) propose a Decision Tree-based algorithm, that utilizes GSM and WiFi traces for transportation mode detection. The algorithm infers a user's mobility, being either dwelling, walking or driving.

Zheng *et al.* (2008) propose an approach based on supervised learning to infer transportation modes from GPS logs. The authors present a graph-based post-processing algorithm, that considers both the constraint of real world and typical user behavior based on location in a probabilistic manner. The approach focuses on transportation modes including driving, walking, taking a bus and riding a bicycle.

Miluzzo *et al.* (2008) present a rule learning algorithm to determine whether a smartphone user is sitting, standing, walking or running. The algorithm is based on accelerometer data. The derived classifiers execute in part on the phones and in part on the backend servers to achieve scalable inference.

Reddy *et al.* (2010) propose a classification system that uses a mobile phone with a built-in GPS receiver and an accelerometer. The transportation modes identified include whether an individual is stationary, walking, running, biking, or in motorized transport. The classification is composed of a decision tree followed by a discrete Hidden Markov Model.

Stenneth *et al.* (2011) propose an approach to inferr a mode of transportation based on the GPS data collected via smartphones and the underlying transportation network data. The algorithm can detect various transportation modes including car, bus, train, walking, biking and stationary. Five different inference models, Bayesian Net, Decision Tree, Random Forest, Naïve Bayesian and Multilayer Perception, are tested in the reported experiments.

Xiao *et al.* (2012) propose a transportation mode detection algorithm that uses the speed statistics derived from GPS and cellular network information, together with statistics obtained from accelerometer samples. The algorithm uses decision tree rules and can distinguish between bus, Mass Rapid Transit (MRT) and taxi.

Montoya *et al.* (2015) designed a system to infer multi-modal itineraries from a combination of smartphone sensor data (e.g., GPS, WiFi, accelerometer) and the transport network infrastructure data (e.g., road and rail maps, public transportation timetables). In the first phase, the algorithm uses a dynamic Bayesian network based on network and sensor data, and can distinguish between walking, biking, road vehicle, and train. The second phase attempts to match parts recognized as road vehicle or train with possible bus, train, metro, or tram based on their timetables.

Chen and Bierlaire (2015) propose a probabilistic method for inferring the transport modes and the physical paths of trips. This method uses data from GPS, Bluetooth, and accelerometer

smartphone sensors. The method is based on a smartphone measurement model that calculates the likelihood of observing the smartphone data in the multi-modal transport network. It is formed of a structural travel model that captures the dynamic of the state of a smartphone user in the transport network, and sensor measurement models that capture the operation of sensors. The approach distinguishes between five transport modes: walking, biking, car, bus and metro. The performance of the approach is analyzes by the similarity indicator (SI) proposed by Bierlaire *et al.* (2013).

Sonderen (2016) focuses on accurate determination of the transportation mode while minimizing the strain on the phone's processor and battery. The data from the internal sensors such as accelerometer, gyroscope and magnetometer are used. The authors evaluate the performance of several algorithms, such as Decision Trees, Random Forest and k-Nearest Neighbors. The most satisfactory results are obtained using Decision Trees. In this paper, the transportation modes are limited to walking, running, riding a bike and driving a car.

3.2 Evaluation

A summary of general characteristics of the approaches is provided in Table 1. Accuracy in Table 1 is defined as the ratio between the number of correctly classified instances of mode m and the number of instances classified as mode m. The duration of test data and the number of participants (journeys/path sequences) in the experimental phase of the approaches is reported in Table 2.

The comparison suggests that one or two sensors are typically used in most of the studies. The GPS and accelerometer are the most widely used sensors for transportation mode detection. The accelerometer is particularly attractive, given that it captures relevant features while being energy efficient. The studies that use three or more smartphone sensors are quite rare. The accuracy of transportation mode detection is higher if more data sources are utilized, as expected. External data sources are rarely employed, and typically include transportation network data and timetables of public transportation services.

The features used in the classification task depend on a given sensor and the classification techniques considered in the studies. It is preferable to use as few features as possible in order to minimize the computational burden of feature extractions as well as the risk of model over-fitting.

Generative models are better suited for the case when mobile phones are used only as a sensing system and the data analysis and classification are performed on back end servers. If the

detection is intended to run on mobile devices directly, generative models are less popular due to their computational costs in contrast discriminative models. In this case, the approaches based on Decision Trees appear to be the most suitable for achieving satisfactory accuracy while using the least resources.

The studies usually focus on stationary, walking, biking and motorized modes. In general, walking and stationary modes are predicted with higher accuracy compared to other modes. Contributions that achieve high accuracies typically consider a unique motorized transport mode. This is not surprising given that a key challenge in transportation mode detection appears to be the differentiation between motorized classes such as bus, car, train and metro. With multiple motorized modes, the detection problem becomes more difficult due to common characteristics that these modes share (e.g. the average speed and accelerations). The studies that employ external data have demonstrated their added value in detecting various motorized transportation modes. Public transportation modes are only considered and detected when external data sources are combined with smartphone sensor data. External data appears to be effective for improving the accuracy of detecting running and biking as well, which can be similar to driving.

Most data sets and sample sizes used in the reported studies are rather small. This may question generality and statistical significance of reported results.

The most satisfactory accuracy is achieved by the approach proposed by Stenneth *et al.* (2011), when taking into account all of the above-mentioned characteristics. This approach demonstrated that Random Forest yields higher travel mode prediction accuracies, when compared to other methods. This finding is also supported by other studies, including Abdulazim *et al.* (2013), Ellis *et al.* (2014), Shafique and Hato (2015).

4 Conclusion

This paper presents a review of transportation mode detection approaches based on smartphone data. The approaches considered in the study differ in therms of the type and the number of used input data, (ii) the considered transportation mode categories and (iii) the algorithm used for the classification task, which affect their prediction capabilities. Clearly, the accuracy of transportation mode detection is higher if more data sources are utilized. The review reveals the necessity of external data for the detection of various motorized transportation modes.

Interestingly, GSM logs provided by the operators are not used for transportation mode detection. This data set is coarse-grained, and its combination with external sources might potentially solve

Table 1: Characteristics of the evaluated approaches

Source	Modes	Smartphone data	External data	Algorithm	Accuracy
Patterson *et al.* (2003)	Walking Bus Car	GPS	GIS	Bayes Model	84%
Muller (2006)	Walking Stationary Car	GSM	/	Artificiel Neural Network **Hidden Markov Model**	Average: 80% Walking: 87% Stationary: 98% Car: 75%
Sohn *et al.* (2006)	Walking Stationary Driving	GSM	/	Naïve Bayes Support Vector Machines heuristic-based methods **2-stage boosted Logistic Regression**	Average: 85% Walking: 70.2% Stationary: 95.4% Driving: 84.3%
Reddy *et al.* (2008)	Walking Stationary Biking Running Motorized	GPS Accelerometer	/	Naïve Bayes Support Vector Machines Decision Trees k-Nearest Neighbors Continuous Hidden Markov Model **Decision Trees** **and Discrete Hidden Markov Model**	>90%
Mun *et al.* (2008)	Walking Stationary Driving	GSM WiFi	/	Decision Trees	Average: 88% Walking: 90.17% Stationary: 90.26% Driving: 87.83%
Zheng *et al.* (2008)	Walking Biking Driving	GPS	/	Graph-based	Average: 76.2% Walking: 89.1% Biking: 66.6% Driving: 86.1%
Miluzzo *et al.* (2008)	Sitting Stationary Walking Running	Accelerometer	/	JRIP rule learning	Average: 78.9% Sitting: 68.2% Stationary: 78.4% Walking: 94.4% Running: 74.5%
Reddy *et al.* (2010)	Walking Stationary Biking Running Motorized	GPS Accelerometer	/	Naïve Bayes Decision Trees k-Nearest Neighbors Support Vector Machines k-Means Clustering Continuous Hidden Markov Model **2 stage Decision Tree** **and Discrete Hidden Markov Model**	Average: 93.6% Walking: 96.8% Stationary: 95.6% Biking: 92.8% Running: 91% Motorized: 93.9%
Stenneth *et al.* (2011)	Walking Bus Car Train Stationary Biking	GPS	GIS	Naïve Bayes Decision Trees Bayesian Network Multilayer Perception **Random Forest**	Average: 93.7% Walking: 96.8% Bus: 88.3% Car: 87.5% Train: 98.4% Stationary: 100% Biking: 88.9%
Xiao *et al.* (2012)	Mass Rapid Transit Bus Taxi Running	GPS GSM Accelerometer	/	Decision Trees	NA
Montoya *et al.* (2015)	Walking Biking Bus Train Tram Motorized	GPS WiFI Accelerometer GSM Bluetooth	Road maps Rail maps Public transport schedules Public transport routes	Dynamic Bayesian Network	Average: 75.8% Walking: 91% Biking: 36% Bus: 80% Train and Motorized: 81% Tram: 91%
Chen and Bierlaire (2015)	Walking Biking Car Bus Metro	GPS Bluetooth, Accelerometer	Open Street Map	Probabilistic method	SI>90%
Sonderen (2016)	Walking Running Biking Car	Accelerometer Gyroscope Magnetometer	/	**Decision Tree** Random Forest k-Nearest Neighbors	98%

Table 2: Test data

Source	Test data duration	Number of users (u) / journeys (j) / sequences (s)
Patterson *et al.* (2003)	12 hours	1 u
Muller (2006)	323 hours	3 u
Sohn *et al.* (2006)	1 month	3 u
Reddy *et al.* (2008)	20h	6 u
Mun *et al.* (2008)	13 hours	2 u
Zheng *et al.* (2008)	10 months	65 u
Miluzzo *et al.* (2008)	4 hours	8 u
Reddy *et al.* (2010)	50 days	16 u
Stenneth *et al.* (2011)	3 weeks	6 u
Xiao *et al.* (2012)	NA	NA
Montoya *et al.* (2015)	42.5 hours	87 j
Chen and Bierlaire (2015)	NA	36 s
Sonderen (2016)	NA	2 u

the issue of sparsity of observations. Also, water transportation modes are not considered in the reviewed approaches, even though this mode represents a regular public transportation system in many countries. These two aspects represent interesting directions of future investigations. The development of techniques able to extract a relevant and optimal set of features is yet another aspect missing in the literature. Additionally, there are several data sources that were not exploited in the reported studies. They include census information, or data about the current day, month or season, and associated weather conditions, and can be used to provide information on the usage patterns of different transportation modes. Also, models can adopt the real time traffic information observed from sensors such as loop detectors. Exploitation of innovative information provided by additional sensors such as temperature, humidity sensor or barometer can result in more powerful transportation mode detection. Studies with lager samples and over a longer time period could confirm the reported results and lead to wider acceptance of the proposed methodologies. Further analysis could investigate the effect of various data collection frequencies on the classification accuracy of the used algorithm as well as the computational costs incurred. Moreover, understanding the role of population heterogeneity in transportation

mode detection could be considered in future research (e.g. variation in data and classification accuracy among different users).

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