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Passive tracking of passengers to analyse public transport use in case of disturbances

Alessio D. Marra · Henrik Becker · Kay W. Axhausen · Francesco Corman

Abstract We tackle the problem of understanding multimodal passenger flows to better address mobility. In particular, we use large scale, long-term GPS passive tracking of travellers, to improve public transport operations in urban areas. We combine this with realised operation data from a transit operator. We develop an unsupervised tool able to detect passengers' travel behaviour and the exact public transport means they took, without any assumption on the frequency of GPS data. Furthermore, we show the significant advantage of using past user data to improve the detection algorithm, in particular to identify the points where users transfer. We test this approach in Zürich and refer to the multimodal mobility supply available there. Ultimate goal of this ongoing work is to understand from realised mobility how passengers react to disturbances, especially for working days and peak hours, and to the mitigation action undertaken by operators in case of disturbances, in order to design good and effective mitigation actions.

Keywords Tracking · travel survey · public transport operations · GPS · mode detection · vehicle imputation · disturbances identification

1 Introduction

Urban areas are related to agglomeration effects of inhabitants and economic value, and this trend is increasing. Mobility is a necessary service, for which people have stringent economic and quality constraints, and increasing service level targets. To achieve both, the entire mobility supply has to be considered,

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where public transport and collective mobility might have a large role. To understand some of those trends, travel diaries have been the primary source of information on the dynamics of travel behavior capturing activity chains, trip patterns, mode choice and time use. Due to their high response burden, traditional pencil-and-paper or telephone-interview surveys (which both are still widely employed) typically ask respondents to report one randomly chosen day only. Moreover, a lot of effort and time are required to conduct them and they represent only a partial view of the whole dynamic behaviour. However, it has already been shown that intra-person variability constitutes a substantial share of overall variation in travel behavior (Pas and Sundar (1995)), which limits the political and operational value of one-day data (Jones and Clarke (1988), Susilo and Axhausen (2007), Schlich and Axhausen (2005)).
With this study, we aim to understand the behaviour of people by long-duration passive tracking, without requiring any efforts from them and without affecting their daily life. In this way, the use of locational data provided by smartphones can reduce drastically the efforts to conduct travel surveys, widening the scale of the observations and leading to a better representation of the whole phenomenon. One of the drawbacks of smartphone-based tracking systems is that energy-intensive GPS services may affect the battery cycle of the smartphone. In fact, a high frequency of position requests can drastically shorten the battery life, making it impossible to track users for a longer time. To overcome these problems, we designed a low-battery consuming smartphone application that passively collects location information with a low sampling frequency, invisible to the user. Then, we designed different algorithms to understand the user's travel behaviour and to deal with low-quality locational data. In particular, we focused on activity and trip identification, mode detection and vehicle imputation. The proposed mode detection algorithm does not require any additional information from the users, it is completely unsupervised, it does not rely on a statistical inference model and it is also able to identify the exact public transport means a user took. In addition, we show how it is possible to understand the users' behaviour in case of disturbances in the public transport network.
The key contributions are:

- Multi-modal transport operations are considered in a fully integrated way
- Large scale, long duration passive tracking data of travellers are collected
- User's travel behaviour is derived from low-frequency GPS data, collected by a smartphone application invisible to the user
- Mode detection and vehicle imputation are estimated by cross analysing tracking data with realized transit operations
- User's past travel information are used to improve the mode detection

The data collection of our study is based on a period of four weeks, during which the smartphone applications passively collected users' location information approximately every 30 seconds. During this period, no respondent interaction was required apart from a short entry questionnaire and installation of the app. Moreover, we collected the realised public transport operations data of the city of Zürich during this period. Then, activity detection, trip segmentation, mode choice and vehicle imputation are performed in a completely unsupervised manner.

The paper is organized as follows: in section 2, the main related works are described, even if a short literature review is presented at the begin of other sections, as each step of the GPS data processing can be seen as unrelated to the others. In section 3, the smartphone application used, the survey process and the whole dataset are described in detail. In section 4, the data cleaning procedure, performed before analysing the GPS data, is discussed. Section 5 presents the trip and activity identification algorithm. Section 6 describes the trip segmentation algorithm, that divides each user's trip in walks and stages. Section 7 shows the mode detection algorithm and the final results. Section 8 describes how understand the user's behaviour in case of disturbances. Then, in section 9 there are the conclusions.

2 State of the art

GPS loggers opened new doors to collect longer-term travel diaries at a substantially lower response burden (Stopher et al (2008)). Data collected with GPS loggers mounted in private cars also showed that traditional survey methods were prone to substantial under-reporting of trips (Bricka and Bhat (2006)) limiting the validity of their results. First studies using personal GPS loggers for travel diary collection were very promising, although a substantial administrative effort was required for distribution of the devices and a prompted recall to obtain additional information necessary to interpret the GPS records (Bohte and Maat (2009); Oliveira et al (2011); Schuessler and Axhausen (2009); Montini et al (2014)). Lately, the focus has shifted away from GPS loggers towards smartphone apps to collect travel diaries (Cottrill et al (2013)). Besides the benefit of an easier survey administration, respondents are also less likely to forget to take their smartphone along for a trip (compared to GPS loggers). Moreover, various systems have been developed for the transport mode detection based on GPS data collected by smartphones (two related literature reviews are Wu et al (2016), Nikolic and Bierlaire (2017)). So far, most smartphone-based tracking systems use a prompted recall approach: in this setting, respondents are asked to manually add further details such as trip purpose, mode, group size, transit fare, parking fees etc. to each trip. Although some systems already employ forms of statistical learning to make suitable suggestions, a substantial amount of user interaction to annotate or validate trip information is still required. Other approaches based on passive tracking, with particular focus on transit, have been focusing on smart card data. In those cases, mode choice, vehicle choice, and even timing cannot always be precisely established (see for example the review of Pelletier et al (2011)).

So far, most of these methods have been tested on small datasets: for instance, Tsui and Shalaby (2006) collected 60 trips with the help of students; Stenneth

et al (2011) recorded information about three weeks for six people. The only works based on a dataset of considerable size, rely on dedicated GPS devices, making the collection of the data more complicated and expensive. Zheng et al (2010) collected information of 65 people for a period of 10 months and Schuessler and Axhausen (2009) build a dataset from 4882 people (requiring multiple waves to limit the number of devices).
Among the studies concerning the automatic mode detection from GPS data, some authors (Schuessler and Axhausen (2009), Stopher et al (2005), Zhu et al (2016), Zheng et al (2010), Zhang et al (2011)) addressed transport mode detection by dividing the problem in different sub-tasks (with small variations among them):

- Data Cleaning
- Trips and Activities detection
- Trip segmentation
- Mode detection

Also this paper follows this structure. Since these tasks are often considered as separate problems, at the begin of each section a short literature review is introduced.

3 Smartphone Application and Dataset

To allow collection of long-term travel diaries with minimal respondent interference, a new smartphone app, the *ETH-IVT Travel Diary*, was developed. The app was tested in a field trial with students at ETH Zürich. Analyses in the following sections are based on the records from this field trial.

3.1 App Design

As described above, the primary purpose of the app is to collect travel diary data during multiple weeks or even longer periods of time. Hence, to keep response burden at an acceptable level, the app has to be minimally intrusive in that it must not require regular interaction with the respondent or substantially affect the device's battery life. With respect to battery life, this means that the sampling frequency cannot be set arbitrarily high. Yet, because data is acquired during a long duration and because travel behaviour follows regular patterns (Susilo and Kitamura (2005)), lower sampling rates can be afforded. Taking into account these design considerations, a passive tracking app with minimal user interaction was developed. Respondents can download it from Google Play store[1]. The user interface only consists of a brief description of the study, a field to enter the respondent's individual ID and a button to start data collection. Once launched, data collection is performed in a background

[1] An iOS version of the app is under development.

process, which remains active until the end of the study period. Even after restart of the smartphone, data collection will resume automatically. During the study period, a notification is displayed reminding respondents of the ongoing data collection. At the end of the study period, the app shows a notification to remind the respondent to uninstall the app.
As direct access to the device's GPS is not possible, *ETH-IVT Travel Diary* requests location data from Android's internal location services. To reach an optimal tradeoff between data quality and battery consumption, a three-layer approach was used:

- *high-priority* requests every 45 seconds,
- *low-priority* requests every 15 seconds,
- *zero-priority* requests every second.

It is important to note that update of location information is at discretion of Android's location services. Typically, location is determined using GPS, Wi-Fi and Bluetooth. Update frequency and sensors used usually depend on the frequency and priority of location requests of all apps and varies by operating system version and device. Hence, records are usually more accurate and precise when respondents use fitness trackers or navigation apps in parallel. The app makes further use of such data by the *zero-priority* requests, which skims the latest available location information without triggering an update.
Data was uploaded to a secure server about every six hours. However, in contrast to prompted-recall approaches employed by earlier studies, no interface is provided for respondents to (re)view their records. To allow for flexibility in the survey design, study duration, upload frequency, sampling frequencies and priorities can be configured remotely.

3.2 Data Collection

To complement the travel diary data with additional information on respondents and collect their feedback to the app, a three-step survey set-up was designed:

1. entrance survey capturing information on socio-demographic background, mobility tool ownership and attitudes;
2. four-week travel tracking using the app;
3. (optional) exit survey to collect feedback and for validation of selected records.

Students enrolled in a civil engineering program at ETH ($N = 1209$) were invited to the field test via e-mail in late March 2018. They were promised an incentive of CHF 20 for their participation. No reminder was sent. 102 students signed up for the study, of which 63 hold an Android smartphone and were therefore eligible for the first field trial, which 48 respondents completed. However, for 9 of those respondents, data quality did not allow further analyses. Hence, travel diaries of 39 respondents were used in this paper. They were complemented by the traces of 2 of the co-authors. At the end of the study, 35 respondents completed the exit survey and provided feedback to the app. In total, 1 032 days' worth of travel diaries were collected, which corresponds to an average of 25.2 days per respondent.

Data quality varied substantially between different users. Further analyses will be conducted to study the effect of smartphone user types and devices. Yet, user-friendliness was generally rated high among respondents with 80% stating that battery consumption was acceptable. This is an acceptable result given that apart from performing the tracking, the app requires respondents to have their GPS turned on at all times, which in itself already increases battery consumption.

4 Data Cleaning

GPS technology is widely used in different devices to capture the most accurate position for the users. Nevertheless, it is often error-prone and then it needs a pre-processing phase to correct it. Two main features are used to filter erroneous GPS points: speed and the angle between points. For each point the speed is calculated from the time and the position of the previous point recorded for the user. Points with speed equals to 0 are removed, because it is probable the smartphone merely returned the previous recorded position and not the real one. Furthermore, points with speed $\geq$ 150 Km/h are filtered, as the maximum speed accepted. A second feature considered is the angle between points. In particular, a point that forms a very strict angle with the following and previous points and which is far away from the previous, is considered as fake GPS point that does not represent the real path of the user, but more probably it is a consequence of the loss of signal, urban canyons or other sources of error. For this reason, all points with an angle < 15 and a distance from the previous point > 60 meters are removed. This rule is applied iteratively to all user's points, until any point is removed. After this filtering process, a Kalman Filter is applied to smooth the two space coordinates (longitude and latitude) of the GPS data and improve the quality.

5 Trip and Activity Identification

As the smartphone application is always active, it records the user's position continuously through the day. Therefore, each user's daily data have to be divided in trips and activities. An activity is a sequence of points near to each other, indicating that the user is in the same place for a long period. Instead, a trip is a connection between two activities, representing a movement of the user to a different place.

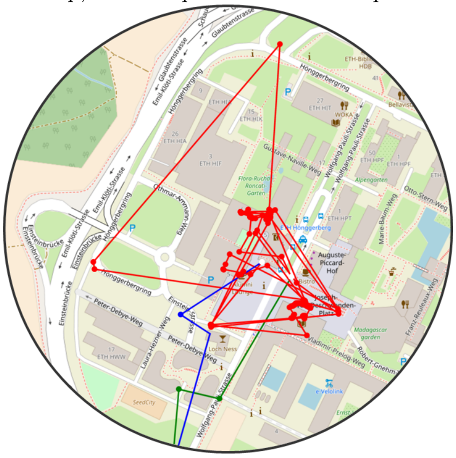
Different techniques have been applied in literature for this problem. So far, all of them are based on the detection of the activities and consequently the trips. One of the most used is the density-of-points based method (Stopher

et al (2005), Schuessler and Axhausen (2009)). Since the recording of the data is continuous as long as the application is active on the smartphone, when a user is standing in one place the application registers a bundle of points near the same place. For that reason an activity can be detected where the density of points in a certain area is greater than a specific threshold. Schuessler and Axhausen (2009) computed a value of density for each GPS point by counting how many of the 30 preceding and succeeding points are within a 15 meters radius. An activity occurs when there is a sequence of points with a density higher than 15 for at least 10 points or 300 seconds.
In this paper, a density-of-point based strategy is used, which has some important differences from those mentioned above. The major one is that the algorithm does not rely on the number of GPS points (like Schuessler and Axhausen (2009)) or on their frequency. In fact, the algorithm can not rely on them, because the frequency of the acquired data is variable due to different factors as the location, the other application in background or the interaction between user and smartphone. For that reason, we define an activity when there are at least 2 successive points for at least 15 minutes in a radius of 250 meters. We choose 2 points because with 1 point it is not known if it is an activity or if no signal has been received. More formally, an iterative algorithm was developed, iterating on each point P: if there are following points in 250 meters of radius for at least 15 minutes, P is the starting point of the activity and the last point in the radius is the ending point. The radius, for each point Q following P, has the center in the average point of all the points from P to Q (excluded).
We choose a very high radius compared to Schuessler and Axhausen (2009) and Stopher et al (2005) (15 and 30 meters), to better deal with the low precision of the GPS data and the position jumps that eventually can occur. Nevertheless, very short walks, starting and ending near an activity, can be considered as part of the activity, because they are still in the radius. It is possible that the first and last points of an activity are in reality points of the previous or following trip, so two rules are added to the algorithm to better assign these extreme points. After that an activity is found, the middle point is computed as the average of the coordinates of its points.

- If the distance from the starting point to the middle point is greater than two times the average distance of each point to the middle point, an activity is not identified and the algorithm tries from the next point.
- If the distance from the end point to the middle point is greater than two times the average distance of each point to the middle point, check the second-last as the ending point.

Figure 1 shows an example identification of an activity. In particular, the first and last points, relating the user's arrival and departure, are not included in the activity, even if they are in the radius and they are not the farthest from the center.
Furthermore, in case of multiple erroneous recording of GPS position, caused often by detecting the position near cell sites or antennas, an additional rule

Fig. 1 Activity identification: The red points are in the activity, the green points are the last points of the previous trip, the blue points are the first points of the following trip.



is added to avoid the detection of false positive trips: a trip with origin and destination closer than 250 meters and with a duration less than 5 minutes, is merged between the previous and following activity to one single activity.

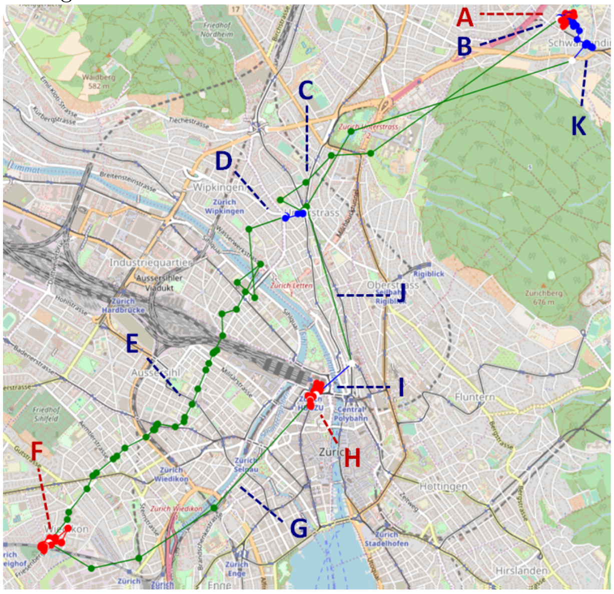
6 Trip Segmentation

The trip segmentation process consists of partitioning of the users' trips in walks and stages. A walk occurs when the user is walking or he is just waiting for a means of transport in a single place, while a stage is a movement of the user done with the help of a transport means, that can be a car, a bus, a train, a bicycle or other vehicles. This step is the most challenging part of the mode detection process, in fact, there is not a common solution in literature to address this problem and different studies used different sensors or they rely on a high sampling frequency for the GPS data.

The most relevant feature, on which all the trip segmentation algorithms found in literature are based, is speed. For instance, Biljecki et al (2013) considered the stops of the user as potential transition-points between two different modes. A stop is detected when consecutive points in an interval of 12 seconds do not have a speed higher than 2 km/h. Gong et al (2012) applied several rules to identify a walk segment, and most of them rely on the speed of the points. Between two different transport modes the user usually walks or stops for a certain period, so Zheng et al (2010) considered a threshold of speed and of acceleration to divide the points in walks and non-walks, then it merges segments of points of the same type according to rules depending on the length of the segments. A paper using a similar procedure is Zhu et al (2016), that applies a label specification step to mark the points as walk or non-walk according to two threshold values of speed and acceleration. Then the label of each point

is adjusted according to the near points: if at least M (value dependent by the number of points) of the previous and posterior points have a different label, change the label of the point. Zhang et al (2011) identifies different stages looking for stops. It considered the heading change as a main parameter for the identification of stops, because stops are usually accompanied with large magnitude values in heading changes. Furthermore, Liao et al (2006) used also GIS information for trip segmentation, in particular the proximity to transition locations such as a bus stop. However, this information can not be used in this case, because Zürich has a high density of bus stops and the GPS error can be very high.
The GPS data recorded for this study have a low sampling frequency that is not fixed and it can vary considerably with different paths or users, so the algorithm developed can not rely on the frequency or on the number of points. Furthermore, the heading change and a derived acceleration are not usable for this purpose with this sampling frequency. A specific segmentation algorithm able to deal with irregular sampling frequency and based only on the GPS position and a derived speed had to be designed. Before computing the trip segmentation for each trip, if in a trip there is an absence of signal for more than 10 minutes, it is divided in two different trips. This time is considered as a threshold to avoid error during the segmentation. Our trip segmentation algorithm aims to divide a trip to a sequence of walks and stages (transfers are considered as walks). It is based firstly on a label specification step, similar to Zhu et al (2016), but considering the adjacent points according to time and not to the number of points. Then, the consecutive points of the same type are grouped in sequences, and these latter are merged according to rules depending on duration, distance and speed. The details of the segmentation algorithm can be found in Marra et al (2018).
There are few cases in which the trip segmentation will fail: a fast run can be detected as a stage; a rapid change of bus, with the second one departing quickly after the arrival of the first one, can be detected as a single stage; a vehicle stuck in traffic for a long time can be detected as a walk. To overcome these problems, the information obtained from the following mode detection algorithm will be used to improve the trip segmentation. This is explained in Section 7.
An example of these steps until the trip segmentation, can be seen in Figure 2. The user's real path is the following: from the activity **A** the user had a short walk (**B**) to take a tram (**C**). Then the user waited for a bus in **D**, took the bus (**E**) and arrived at **F** to stay there a while. Later the user took a train (**G**), stayed at the Zürich Main Station (**H**), walked to a stop (**I**), took a tram (**J**) and walked to home (**K**). Even if the sampling frequency is different through the day, the segmentation algorithm is able to divide correctly each trip. In particular, the frequency is lower when the user is on a train (**G**) or in a tunnel (the upper-right part of **C** and **J**). It is also lower on **I**, probably because the main station has a underground part.

Fig. 2 Trip segmentation of a user's day (from A to K): activities (red), stages (green), walks (blue). The table gives the average time between two points (sampling frequency) for the segments and the activities.



	Average Time (s)
A	76
B	85
C	56
D	29
E	21
F	25
G	124
H	53
I	312
J	264
K	53

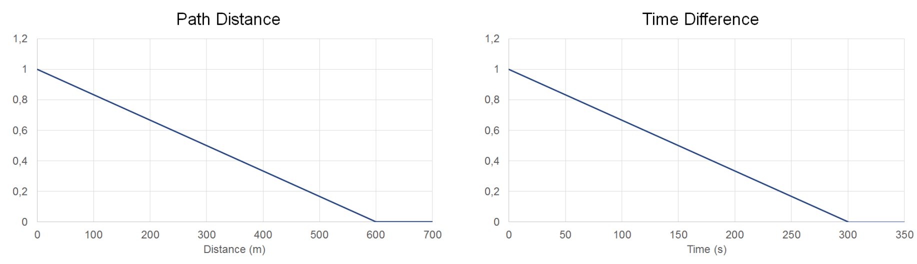
7 Mode Detection

Many methods have been studied to automatically collect information about the user's travel behaviour from raw GPS data. One of the major problem is the identification of travel mode. In the first papers the GPS data have been collected with the help of dedicated GPS devices (Patterson et al (2003), Gong et al (2012)), that are expensive for the researchers and cumbersome for the users. In the last decade, researchers started to look at smartphones as a powerful source of data for travel surveys. In fact, they are equipped with a GPS module, most of the people travel always with one of them, and they have also other sensors that can be useful for this purpose. However, the battery life is still a problem (Wu et al (2016)), especially when a high sampling frequency is specified. For this reason, we developed an approach able to deal with a low sampling frequency.

One of the most recent review of transportation mode detection using GPS data collected by smartphones is presented by Nikolic and Bierlaire (2017). They stated that there are two categories of methods for mode detection: machine learning methods and hybrid methods, also relying partially on machine learning techniques or probabilistic models like Hidden Markov Models (Reddy et al (2010)). Wu et al (2016) made a similar systematic review and it asserted that the methodology adopted by the reviewed works is rather similar. First, some features are extracted from the sensors, then a training set is

built to train a machine learning algorithm, and then the algorithm is used to predict unseen data. For instance, Zheng et al (2010) proposed a supervised learning approach, using a decision tree, to infer transportation modes from GPS data. It is able to detect walking, driving, taking a bus and riding a bike. Stenneth et al (2011) compared different inference models like Bayesian Net, Decision Tree, Random Forest, Naive Bayesian and Multilayer Perceptron. It is able to detect different transport means as car, bus, train, bike, walking and stationary. Furthermore, it rely not only on the GPS data, but also on transportation network data. Reddy et al (2010) built its classification system using also accelerometer data in addition to GPS data and it is able to detect among stationary, walking, running, bike or motorized transport. It used a hybrid approach based on a decision tree and a Hidden Markov Model. Montoya et al (2015) build a system based on a Bayesian network to infer the transport mode from smartphone data (GPS, wifi, accelerometer) and transport network information like the public timetable. Finally, Patterson et al (2003) presented a Bayesian model inferred in an unsupervised manner. It can distinguish between walk, drive or taking a bus and it also showed that the use of additional knowledge like bus stop location can improve the algorithm.
Except Patterson et al (2003), all of the mentioned studies rely on inference models that need a training set to work. For this reason a manual labelling of the transportation modes is required, that can be expensive or difficult to obtain, limiting the dimension of the dataset. In addition, most of the mode detection studies in the literature lack information about the sampling frequency of the GPS data or did not compare their algorithm with different sampling frequencies. Instead, in this study we consider this parameter crucial for a mode detection algorithm, because only with a low sampling frequency, the battery of the smartphone is not affected and then the algorithm can be used in practical applications. Therefore, for our purpose to have a system invisible for the users and that can easily work with a large number of people, we choose a data-driven approach largely different from the previous papers.
One of the most important differences is that the algorithm is completely unsupervised and it does not use any statistical inference model. In fact, it is mostly based on the realised operations data. Only Stenneth et al (2011) of the cited works used this type of data, but just to build features for their inference model. For buses, trams and trains travelling in the city of Zürich the realized data are publicly available (SBB (2018)): more specifically, for each stop of each vehicle the scheduled and realized times of its arrival and departure are available. Since walks are detected during the trip segmentation, the mode detection is able to label a stage as a bus, tram, train or otherwise a private vehicle. Moreover, for the public transport it detects the exact vehicle that the user took.
The algorithm starts as following: all the public transport stops in a radius R near the starting point of the stage are detected, then all the vehicles that are stopping at one of these stops in $\pm$ T seconds from the starting point are selected. The same method is applied for the end point, then the intersection of the vehicles in the two groups returns a list of all the vehicles passing near

Fig. 3 Mode detection likelihood: The two sub-functions *PathDistance* and *TimeDifference*.



the user at the begin and at the end of the stage. At this point, a likelihood function is applied to each element of the list to select the most probable vehicle the user took. Instead, if the list is empty, that means the user used a private vehicle. For the experiments in this paper the parameters have been set to T = *250 [sec.]* and R = *max(250,min(accuracy,400)) [m]* where accuracy is a value in meters provided by the smartphone for each GPS point.

7.1 Likelihood function

The likelihood function for the mode detection is a combination of two functions comparing the paths of the user and of the vehicle, as shown below:

$$L = \lambda * TimeDifference + (1 - \lambda) * PathDistance$$

TimeDifference is the sum of the difference between the departure times and the difference between the arrival times of the user and the vehicle. *PathDistance* is the average euclidean distance between the user's points and the vehicle points. The vehicle points are calculated at the same timestamps of the user's points interpolating from the arrival time at each stop. Then, these two values are scaled like in Figure 3 to be comparable. A value of $\lambda = 0.5$ is chosen because using only the *TimeDifference* can bring to false positive matching with vehicles that had a different path, meanwhile the *PathDistance* is not reliable if there are few user's points. In the end, the value L is multiplied by the times that the vehicle appeared in one of these lists of candidate vehicles of stages in the same trip. The idea behind is that if a single vehicle is a candidate to match different stages of the same trip, it is probable that the user took only one vehicle to make all the stages.

7.2 Mode detection improvements

In order to improve the mode detection algorithm and to overcome the errors obtained during the trip segmentation, three different rules are applied:

Table 1 Dataset information: values of the different components obtained applying the whole mode detection algorithm to the dataset.

	Quantity
Activities	2931
Trips	2820
Walks	7031
Stages	4868
Detected stages	1954
Not assigned stages	522
Far stages	2392
Past Data Detected stages	128

– If in a trip there is the pattern *stage-walk-stage* and the two stages are not assigned to a means, consider the three segments as a single stage and compute the mode detection.
– If in a trip there is the pattern *stage-walk-stage* and the vehicle detected for the two stages is the same, consider the three segments as a single stage performed with that vehicle.
– If a stage is not assigned to a means, look in the user's past data for a possible transfer point in the path, and try to detect two different means for the whole stage.

The first two rules are introduced in case of a wrong detection of a walk segment. For instance, this can happen if a vehicle is stuck in traffic. The last rule is introduced in case of a walk segment is not detected, that can happen if a transfer is performed quickly. In this case, the average point of the previous activities and the starting and ending points of the previous stages of the user are considered as potential changing points, if they are in a distance R (250 m) from one point of the user's path. If some of these changing points are near to each other (250 m), the average point is considered, because they represent the same location. This represents a first attempt, never described in literature, to use the user's past data for a mode detection algorithm. In that way, only the user's relevant places are considered, useful in particular for datasets spanning multiple weeks with a huge quantity of data recorded for a single user.

7.3 Results

The user's GPS data are recorded over a period of four weeks, then it was not asked to the participants of the experiment to manually label their movements and the travel modes they took in this period. For this reason, a ground truth for the mode detection is not available, but the quality of the algorithm can be assessed comparing the user's path with the path of the detected transport mode. Table 1 gives the results of the mode detection algorithm and the dataset, to give a better idea of its dimension. Regarding the stages, they are divided in three different groups: *detected*, *not assigned* and *far*. A stage is marked as *far* if it is performed partially or completely outside the city of

Zürich; it is marked as *detected* if the mode detection algorithm found a mode for it; instead, it is marked as *not assigned* if the algorithm did not find a match to a means. In this last group there are principally stages performed with a private vehicle, but also public transport stages that are not detected, because of bad GPS quality or errors during the activity identification or trip segmentation steps. Further, in the *detected* group there are also false positive detections, that can occur only in case of data with a very low quality or, for instance, if the user is always behind a bus and then the algorithm match the bus as the transport mode. Nevertheless, this case is considered rare because usually a car can overtake or has a different lane, and a bicycle has a higher travel time. The *Past Data Detected* stages, are the stages detected thanks to the use of the user's past data, as described in Section 7.2. Without using these data, the *Past Data Detected* stages would have been labelled as *not assigned*, with a increase of the *not assigned* group of the 24.5%. This value clearly shows the importance of information about the user's past travel behaviour for a mode detection algorithm.

It is important to notice that the main factor influencing the quality of the mode detection algorithm is the quality of the data, while the sampling frequency is less relevant. In fact, in the extreme case of only two points, with the exact position and time, one at the origin and the other at the destination of a user's path, the algorithm detects if it is a stage from its speed and the exact mode from the departure and arrival times of the modes in the network. To measure the quality of the mode detection, the *TimeDifference* function (described in Section 7.1) is used. In fact, if the difference between the arrival and departure times of the user and of the vehicle is low, it is reasonable to think the detection is correct. The *PathDistance* function was not chosen because a user's path can be very noisy and then not comparable with the path of the detected mode even with a correct detection. The distribution of the *TimeDifference* of all the detected stages in the dataset is shown in Figure 4. This value, the sum of the differences between the arrival times and departure times of the user and the vehicle, is caused by two main factors: the trip segmentation and the sampling frequency. In particular, an erroneous trip segmentation can identify the beginning or the end of the stage at some points before or after the real one. Moreover, often with a low sampling frequency there are no points in the exact time the user took the means. For these reasons a mean value of 91 s and a median value of 68 s for the *TimeDifference*, shown in Figure 4, are considered good values and a guarantee of correct matching. Instead, with higher values, such as more than 300 s, the probability of a wrong detection increase. To increase the precision of the algorithm, it is possible to decrease the values for the parameters T and R, to reduce the wrong detection, but in this way also the false negatives increase. In fact, if for instance the user is in a station, there could be a long time without signal or there are only data with low accuracy, then high values of T and R are required.

In Figure 5 for each detected stage the sampling frequency of the trip and the value of *TimeDifference* is plotted. The sampling frequency of the trip is

Fig. 4 Distribution of *TimeDifference* for all the *detected* stages in the dataset (grouped each 20 *s*)

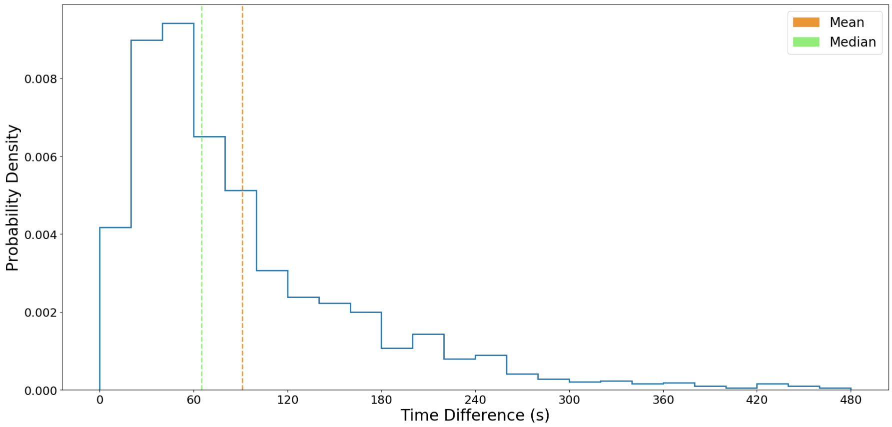
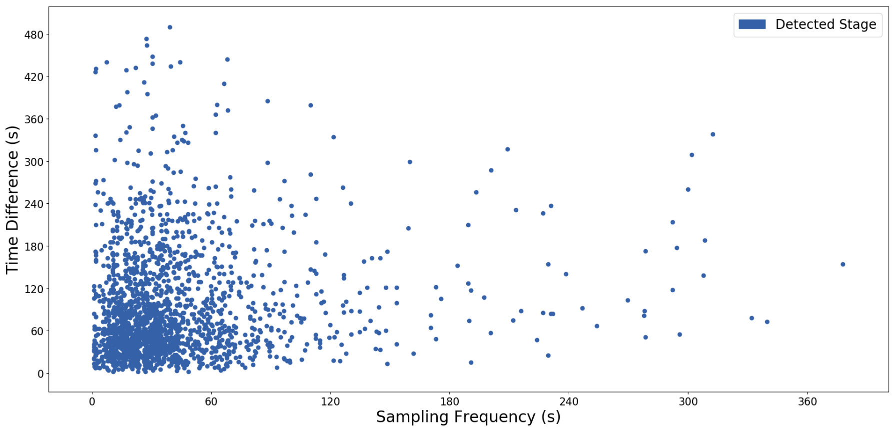
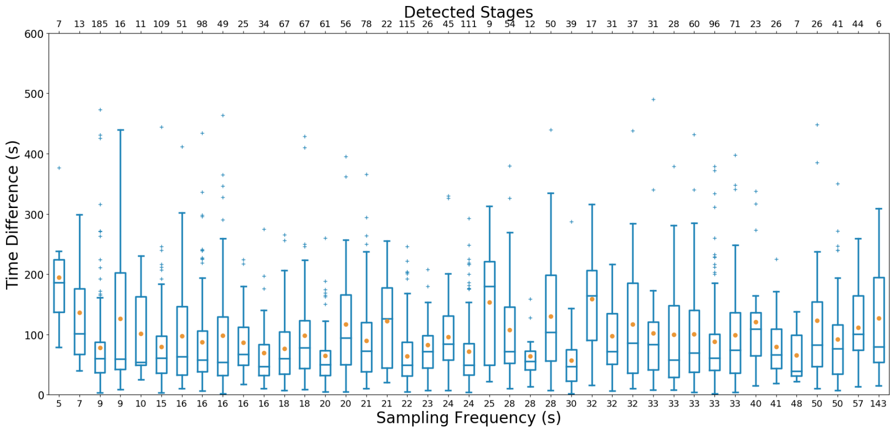


Fig. 5 Sampling frequency and *TimeDifference* for each detected stage.



shown, because the mode detection principally relies on the two extreme points of the stage, that are detected during the trip segmentation. Moreover, gaps of signal greater than 10 minutes are not considered for the sampling frequency as for the trip segmentation. It is possible to see that there is not a specific relationship between sampling frequency and *TimeDifference*, demonstrating that the quality of the mode detection algorithm is not dependent from the sampling frequency. In Figure 6 the *TimeDifference* is grouped for stages of the same user and the average sampling frequency for all users' trip is shown. No relationship has been found between the users' sampling frequency and the mode detection quality, demonstrating that the variation of *TimeDifference*

Fig. 6 Values of *TimeDifference* for all the *detected* stages, grouped by user. The orange dot is the mean value. The number of detected stages and the average sampling frequency for all user's trip are shown.



among different users depends principally on external factors like the user's travel behaviour or his main locations, that can alter the data.

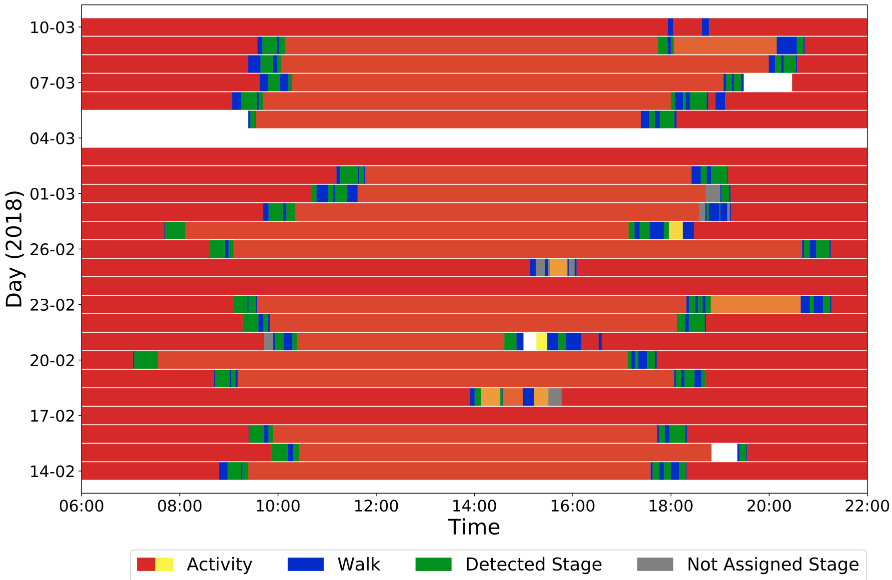
8 User's behaviour in case of disturbances

With the mode detection algorithm described in the previous sections, it is possible to identify the users' main activities and how their trips are performed. In that way, looking in the history of the user's travel data, different mobility patterns can be discovered. In Figure 7 are shown all the movements of a user for 25 days. The user's home and his second main location (workplace) are easily recognizable and there is a clear pattern in the user's morning trips from house to work. There is also the same pattern in the opposite direction in the evening, even if it is less regular than in the morning.

Discovering these patterns, it is possible to detect anomalies in the user's behaviour and then check in the public transport data if there was a disturbance that involved the user's usual transport means. For instance, in Figure 7 the morning trip of 1th March 2018 is two times longer (≈ 56 minutes) than usual (≈ 33 minutes) and it is performed with three different transport means and long walks. In that day, in Zürich it was snowing and most of the streets were closed to traffic, resulting in huge delays and cancelled runs in the public transport network. For that reason, the user had to take a different path longer than the usual route to reach the destination.

During the study period there were no relevant disturbances in the public transport network of Zürich and no respondent has been identified as involved in a major disturbance. Nevertheless, the example in Figure 7 shows how it is possible to understand the users' behaviour in case of disturbances. In par-

Fig. 7 Continuous tracking of a single user for one month. Activities in the same place have the same color, that goes from red to yellow according to the time spent in the activity. A white space indicates absence of signal.



ticular, after detecting users' mobility patterns or common trips, it is possible to detect anomalies and check in the public transport data if there was a disturbance. In that case, it is possible to analyse how the users reacted to the disturbance, if they chose the shortest way, or if they were not informed about it and then they took a long time to react.

9 Discussion and Conclusions

With this work it is confirmed that GPS data collected from smartphones are a powerful means to understand users' travel information, compared to traditional travel survey methods. Moreover, we have overcome the main obstacles that arise using the smartphones for this purpose: we used a low-battery consuming application that does not affect the daily use of the smartphone; we also showed that is possible to collect users' travel information only with low-frequency and low-precision GPS data. In fact, specific algorithms for activity detection, trip segmentation and mode detection have been designed to deal with this type of data. Regarding the mode detection, our technique is totally different from what is found in the literature: in fact, most of the work is based on supervised learning, requiring a lot of efforts to manually label the data. Instead, our algorithm only relies on the combination of user's GPS data with the transportation network data, and it is also able to perform an exact vehicle imputation. Moreover, this paper represents an original attempt to use the realized data of a public transportation network for a travel survey purpose. We also introduced a way to exploit the user's past data to improve the mode detection algorithm. In fact, it is shown clearly that information about the user's past movements and main locations can be used to better understand the user's future behaviour. Finally, we showed how it is possible to exploit anomalies in mobility patterns to identify which disturbances in the network affected a user. With this work we demonstrated the feasibility of build travel surveys with low costs and without any negative impact on the users, opening the way for a future study based on a large scale dataset, that will lead to a different manner to conduct travel surveys. We will be able to extract different patterns and to shed some light on understanding choices of travellers that can not be derived from a small dataset. In that way, it will be possible to analyse why people make some travel choices and what are their main criteria for these choices. In a future work we will also include in the mode detection algorithm a way to distinguish private vehicles between cars and bicycles, based on speed patterns and the user's past data. Furthermore, a future goal will also be to automatically detect mobility patterns and anomalies in the user's travel behaviour in order to better identify disturbances in the transport network and how passengers react to them and to the mitigation action undertaken by operators.

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