

# Urban Sensing: Using Smartphones for Transportation Mode Classification

*Keywords: Transportation mode classification, Vehicle detection, Social sensing, Crowdsourcing, Smartphone, CITYing.*

## **Abstract:**

We present a prototype mobile phone application that implements a novel transportation mode detection algorithm. The application is designed to run in the background, and continuously collects data from built-in acceleration and network location sensors. The collected data is analysed automatically and partitioned into activity segments. A key finding of our work is that walking activity can be robustly detected in the data stream, which, in turn, acts as a separator for partitioning the data stream into other activity segments. Each vehicle activity segment is then sub-classified according to the vehicle type. Our approach yields high accuracy despite the low sampling interval and does not require GPS data. As a result, device power consumption is effectively minimized. This is a very crucial point for large-scale real-world deployment. As part of an experiment, the application has been used by 495 samples, and our prototype provides 82% accuracy in transportation mode classification for an experiment performed in Zurich, Switzerland. Incorporating location type information with this activity classification technology has the potential to impact many phenomena driven by human mobility and to enhance awareness of behavior, urban planning, and agent-based modeling.

# 1. Introduction

“Much of our understanding of urban systems comes from traditional data collection methods such as survey by person or by phone. ... They are hard to update and might limit results to a ‘snapshot in time’ (Reades et al., 2007).”

Urban planners may not satisfy with the data that is collected by the methods such as survey by phone or survey by Internet. This is because surveys usually collect data at a single point in time while modern cities become more complex and exhibit very dynamic conditions. Regarding the survey in transportation, people do not always make exact journey that they described on a survey. It cannot cover every trip, which is limited in to collect average travel of the survey happened. It is also difficult to measure changes unless two or more surveys are done at different temporal instances. People are easily tired of such frequent survey requests. Moreover, this repetition makes surveys expensive, time-consuming, and impractical.

In contrast, an emerging field of research uses mobile phones for “urban sensing” allowing us to collect scientific data in a new and innovative way (Cuff et al., 2008). Essentially, this is a type of “social sensing” with mobile devices enabling data collection from a large number of people in ways that were previously not possible. It provides the opportunity to track multiple data points in real time, and therefore to sample the dynamic behaviour and inherent complexity of human activity within a city. The data points can be used to provide information and services not only to the individual user (e.g., location-based information), but also to urban planners who can use it to gain insight into the relationship between a city’s structure and its internal dynamics; for example, what are the patterns of people movement? how large is a person’s geographic living scope? how effective is a planner-proposed solution within the urban system? In addition, we can characterize the mobility pattern of a city including evaluating efficiency through people's average moving distance, analyzing the change of transportation hot spots, estimating the favorite transportation mode, comparing with other cities, and monetizing the cost of socially-motivated inner-city travel.

Data capturing of human mobility become widely available in the real world by the advance of diverse location sensing technologies (Campbell, 2006). However, despite its importance for urban planning and traffic forecasting, our understanding of the basic individual patterns of real-time human mobility remains limited due to the lack of tools to easily monitor and spatially-locate individuals. Moreover, it is hard to get insight into disaggregated travel styles since there is a lack of a medium or knowledge to automatically classify the different travel modes among the diverse transportation types.

Our belief is that automating the process of obtaining individualized and disaggregated human mobility will increase user participation in urban data collection and improve urban planning. For example, including transportation mode identification enables users to obtain an extended analysis of their travel patterns such as estimation of individualized CO<sub>2</sub> emission or measures of personal contribution to local transportation based on their trip diary. Urban planners will obtain more detailed and real-time observations of urban dynamics. Amongst many other possibilities, it will enable determining under which condition are vehicles or walking preferred and what kind of environmental characteristics affect the transportation choice.

In this context, we exploit an emerging field: *mobile crowdsourcing*<sup>1</sup>. We focus on automatically determining the travel mode used by an individual and analyse it to extract transport information. We

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<sup>1</sup> Mobile crowdsourcing is a term that accounts crowdsourcing activities, which are supported by mobile devices. Thanks to the recent development in mobile devices such as diverse sensors and

have studied approximately 500 sensing samples from anonymous mobile phone users in Zurich, Switzerland whose acceleration measurements are logged during daily activities. For anonymity, all sensing data (e.g., acceleration and location) is collected by randomly generated ID numbers, which doesn't include any personal information.

Our prototype system and method provides answers to the following two key questions.

- ***How to convert a mobile phone's sensor data into transportation information?*** During movement, each travel mode (e.g. car, bus, tram, or train) has a different "signature" (e.g., rolling, waving, vibration, and/or acceleration pattern). Contrary to the general belief that a phone's acceleration measurements contain only information about when a vehicle leaves and stops, we found the cumulative set of acceleration measurements to be a very rich source of information that can be exploited to determine travel activities and transportation choices. Our method automatically classifies the travel mode by continuously inspecting readings from the mobile phone acceleration sensors as well as network-based approximate location data. While developing the transportation mode classification system, we found the heavy use of sensing and data processing to potentially cause fast battery drain. In fact, most previous research in mobility sensing (Hemminki et al., 2013) recognizes the problem of high battery consumption. Thus, to minimize the impact on battery life and to permit long term sensing periods (e.g.. weeks or months), our method focuses on providing a solution that does not use high power-consuming subsystems on a phone (e.g., its GPS system).
- ***How to provide an overall sensing process without disturbing daily phone use?*** The answer demands a fully-optimized design process (e.g., the solution must carefully orchestrate phone sensor types, sensing circles, processing procedure, detection algorithm, and server-user network usage). While most mobile sensing applications require user input, our entire sensing and data acquisition procedure operates in full automation. Users are not required to spend time manually typing out location information. The sensing data is collected and delivered to a central server, which subsequently measures and analyzes their urban activities. The computed results are transmitted back to the mobile phone and optionally displayed, thus providing a visual means to enhance awareness and environmental impact. Furthermore, we highlight two aspects of our approach, "*network-based location sensing*" and "*low-frequency sampling*", both of which help improve battery efficiency and method automation.

Altogether, the main objectives of this article include

- describing a mobile phone acceleration-sensor and network location-based transportation mode detection algorithm which collects information for human mobility,
- creating a prototype and preliminary deployment to collect field data in real urban environments, and
- providing an evaluation of the algorithm accuracy, battery efficiency, and a proposal for future uses and possibilities.

In the following, Section 2 will provide a summary of recent work addressing limitations and related problems. Section 3 will present the overall framework for the implementation, and Section 4 will describe our solution to automatic travel mode classification, and Section 5 will show statistical evaluations of our solution. Finally, we conclude with Section 6.

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wireless network enables smartphone, the crowd-sourced information can be collected and shared without any further difficulties for a larger scale of analysis.

## 2. State of the Art

Urban sensing (Campbell, 2006) enables us to collect scientific data in a new and innovative way. In fact, this is a very useful type of crowd-sourced sensing (Demirbas, 2010), which enables collecting urban data from a large number of people in ways that were previously not possible.

Miller (2013) stated that sensed transportation and geographic information can cultivate transportation systems where participants share information and resources to solve operation accessibility problems. Jane Gould (2013) emphasized mobile phones will bring new opportunities enabling travel surveys as a medium of data collection.

Smartphones offer researchers the possibility to develop “crowdsourcing” applications that collect information from an extensive number of individuals and open the door to studying the dynamics of large populations (e.g., Joki et al., 2007; Murty et al., 2008, Turner et al., 2011). Moreover, smartphone-based data collection is becoming increasingly important to transportation planning (Barbeau 2011, Berlingerio et al., 2013) and to other planning agencies and private firms (e.g., Alt et al., 2010).

Nevertheless, mobile crowdsourcing has not yet become a widespread medium for data collection because most of the existing applications require active user input. Since users typically do not receive any reward for their effort, they quickly lose interest and are not willing to collaborate (Santos et al., 2010). A new research direction, called “social sensing”, collects data without requiring any active user input (Kim et al., 2012; Madan et al., 2010; Adams et al., 2008; Asakura et al., 2005). It is possible to use the sensors and stochastic algorithms on a smartphone to automatically detect certain types of user activity. A related effort is to collect location data from cellular phone tower use (Reades et al., 2007; Becker et al., 2013). This effort enables widespread data collection at low cost. But, the collected data does not possess the information about individualized activities that we seek.

CO2GO, an on-going project in the SENSEable City Lab of MIT, is a smartphone application that aims to sense the transportation mode of users in order to estimate their CO<sub>2</sub> emission level (<http://senseable.mit.edu/co2go/>). Other similar on-going research efforts for detecting individualized transportation mode (Bolbol et al., 2012; Wang et al., 2010) and estimating CO<sub>2</sub> emission are Ecorio (ecorio.org), Carbon Diem (carbondiem.com), and recent work by the Helsinki Institute (Hemminki et al., 2013).

In France, Pluvinet et al. (2012) and its continuous work (Gonzalez-Feliu et al., 2013) investigate urban goods movement using a smartphone application. They show the result in diverse data combinations: characteristics of the travel, CO<sub>2</sub> emission per km and per company, type of road use, and CO<sub>2</sub> emission per street. This is a very good example of how crowd-sourced data is utilized in urban planning.

In Oregon, U.S, the recent project “Emission Model Sensitivity Analysis” (Bell et al. 2013) builds on the past project “Truck Road Use Electronics (TRUE)” to provide improved emissions estimation at the project and regional level. The new project uses mobile phone GPS tracking to correct and evaluate the level of error that might be encountered when such detailed data is not available by the TRUE system. This integration, together with the Oregon Department of Transportation (ODOT), demonstrate high confidence in adopting mobile phone based and hardware-based data collection.

However, all these efforts have two critical issues. First, the methodology used is very battery-intensive. For instance, all the aforementioned systems use GPS technology in order to determine location, compute acceleration values, and perform way finding. Moreover, these systems assume outdoor only usage, moderate to good weather, and high sampling frequency (Krasner, 2010). Thus,

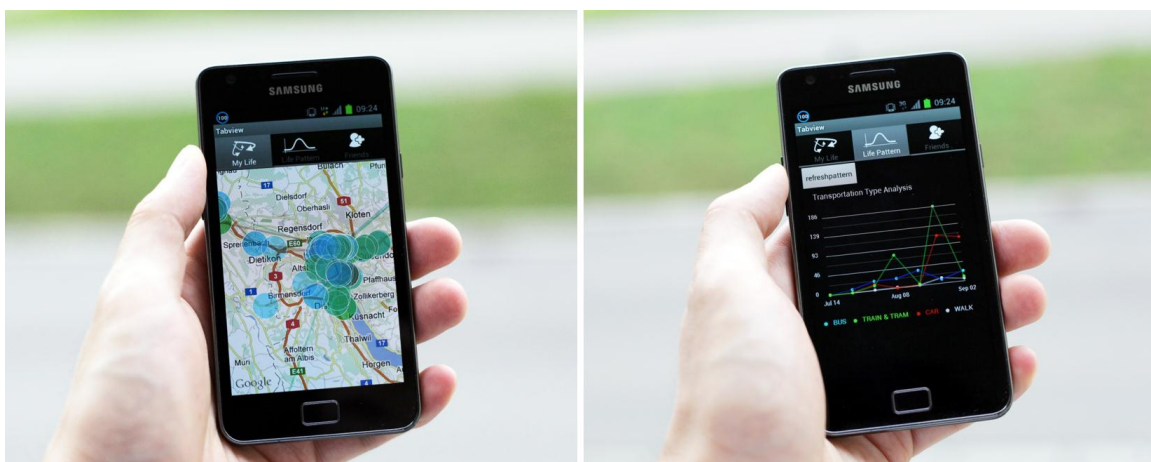
high computing power and battery use is needed in order to obtain precise GPS measurements for estimating movement and acceleration values (Paek et al., 2010). In addition, CO2GO has a fixed sensing rate (25 times per second) and sensing window size range (1.28-5.12 second), which is very demanding on computation and power resources. Further, in order to deduce meaningful patterns of activities, applications need to run in the background for a long period of time. Such power-draining applications are likely to be rejected by the users (Vasileios et al., 2010), as users do not want to compromise the use of their device due to an application that is constantly running in the background. Therefore, it is very important to develop an application that has high efficiency and does not impede the user's daily tasks. Second, none of the systems focus on detecting changes in the transportation mode or on supporting long contiguous segments of transportation analysis (e.g., CO2GO has a relatively short-term sampling window of 1.28 to 5.12 seconds). Hence, these previous methods are less efficient at detecting transportation modes and are not able to robustly indicate the mode during long and contiguous single transportation mode segments.

Our automatic approach determines transportation mode in a more flexible way. The sampling window is dynamic. Thus, it can cover an entire vehicle travel period and it is automatically adjusted based on the activities performed by the individual. While CO2GO performs a short-term GPS-based signal comparison to predetermined templates, our method focuses on the activity context without requiring the GPS. By detecting and using walking as a separator, articulated activities are subdivided to individual activities and robustly classified using an adaptively determined sampling window. Altogether, yielding automatic, high accuracy, and low-power consumption transportation mode analysis.

### 3. CITYing

Our application was implemented and tested on Google's Android platform. Android is among the most popular smart phone operating systems (Jansen, 2011) and primarily adopts the Java programming language. For testing and deployment we used several recent Android devices including Google phones; i.e., Nexus S, Nexus Galaxy, Samsung Galaxy S I9000, and Galaxy S2 I9100.

For development, we used the Eclipse platform, a multi-language software development environment including an integrated development environment (IDE). In addition, we used plugins for supporting Android-specific development.



**Fig. 1. Application GUI.** Snapshots of a subset of the application GUI to control logging. Users simply install and run the application "CITYing". All running processes (e.g., sensor data logging, data transferring, and data analysis and visualization) execute fully automatically.

The devices have acceleration sensors which can measure x, y, z-axis accelerations within a range of +/- 2g and with a sensitivity of 256 LSB/g. A sensor of this type measures the acceleration applied to the device ( $A_d$ ). It does so by measuring forces applied to the sensor ( $F$ ) using the equation:

$$A_d = -g - \sum F / mass$$

Regardless of the mobile phone company and type of sensor device, when the device is sitting idle on a table the magnitude  $A_{tot}$  of the 3D accelerometer reading is approximately  $g = 9.81 \text{ m/s}^2$ . Thus, we subtract  $g$  from all acceleration magnitudes. Most devices use this standard, thus there is no need for device-specific calibration.

Fig. 1 contains images of the CITYing graphical user interface (GUI). The application is launched by the user and remains running in the background, letting other applications run normally. The program then runs continuously in the background until stopped. Sensor data can be retrieved at any time for automated data analysis.

While user can use the application without any user input, we also collect ground truth data during our experimental deployment. Ground truth data collection consists of users keeping a log of their activities – we include travel type buttons in our application that user can simply leave logs of their actual travel types. The log contains three elements per line: time, travel mode, and location. Users noted their activities every time they got on and off a vehicle, and also when they did a non-vehicle activity. Our experimental deployment was within Zürich, and made use of the local trains, tram, buses, walkways, and private cars.

## 4. Travel Mode Detection

Our approach uses the sensing values from acceleration and location sensors, and classifies the transportation modes of the mobile phone user. Concisely, the detection process can be summarised by the following three processes:

- collect and analyse data,
- detect walking segments and use them to partition the overall activities, and
- perform travel analysis with segments having speed greater than 7km/h (i.e., the maximum walking speed as defined by our experiment) and identify the travel mode.

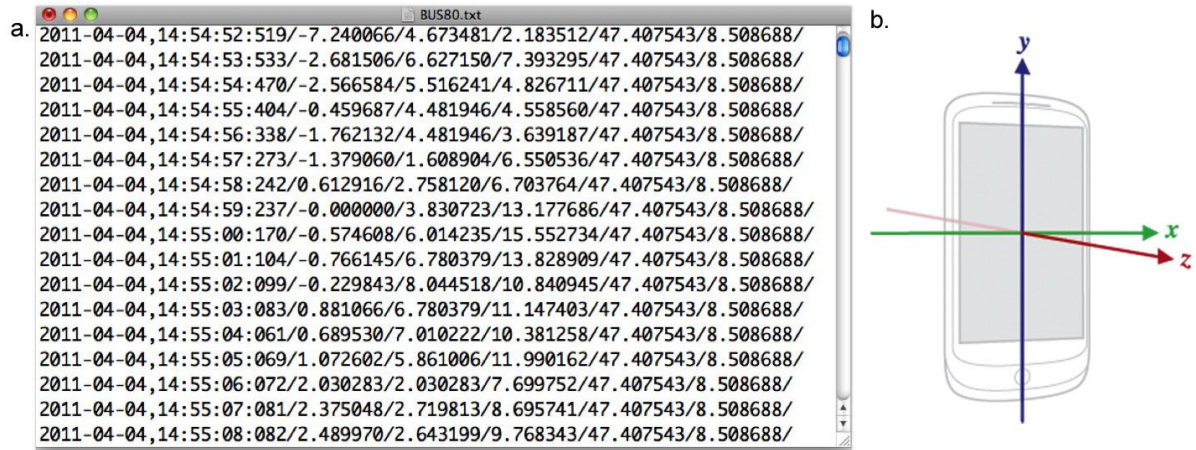
### 4.1 Data collection and analysis

Our prototype application continually logs three fundamental types of data: i) date and time, ii) x-, y-, and z-acceleration values, and iii) latitude and longitude values. Fig. 2a shows an example of the data log file. Each row contains date and time, x-, y-, and z-acceleration values, and network-estimated latitude and longitude readings (year-month-day, hour: minute:second:milli-second/x-/y-/z-acceleration/latitude/longitude/). Fig 2b shows 3D acceleration measure schema. The acceleration sensor measures the acceleration applied to the device, including the force of gravity. When the device is sitting on a table (and not accelerating), the accelerometer reads a magnitude of  $g = 9.81 \text{ m/s}^2$ . Similarly, when the device is in free fall and therefore rapidly accelerating toward the ground at  $9.81 \text{ m/s}^2$ , its accelerometer reads a magnitude of  $g = 0 \text{ m/s}^2$ . Therefore, to measure the real acceleration of the device, the contribution of the force of gravity must be removed from the accelerometer data.

The data is stored locally on each phone (in our prototype implementation) but could easily be transmitted, in real-time, to a database server using the mobile data network services. The logging process continually adds the next reading of the mobile phone sensors. The sampling interval is set

to 1 second by default. The operating system does not guarantee an exact sampling interval, but as our results will show, the jitter is within an acceptable range. The mobile device can be carried in any orientation, so the vector-valued acceleration is converted into a scalar. Therefore, the total acceleration magnitude is calculated as the Euclidean length of the 3D acceleration vector (e.g.,

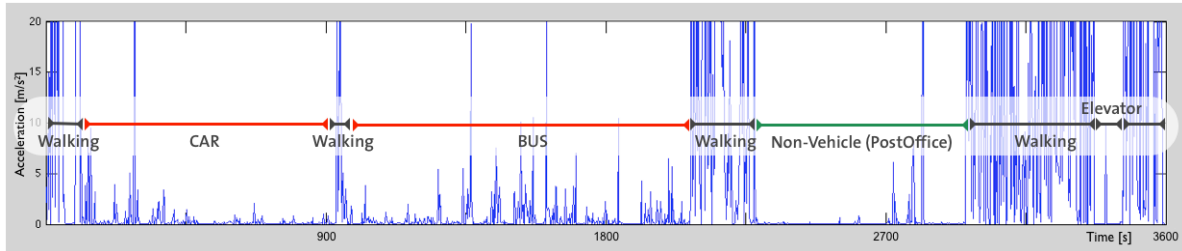
$$A_{tot} = \sqrt{x^2 + y^2 + z^2}.$$



**Fig. 2. Data logging and Sensor Coordinate System** a) Data logging and Sensor Coordinate System. b) 3D acceleration measure schema.

Upon examination of the logged data, we find that user walking can be robustly differentiated from non-walking activities of the phone user. To visualize how the total acceleration values fluctuate during a typical user session, we show in Fig. 3 the logged acceleration signal for an example period of nearly one hour. This is a representation of raw data from a smartphone sensor. The ground-truth activities provided separately by the user have been manually appended at the bottom of the graph. As can be observed in Fig. 3, there are clearly discernable walking activities between each vehicle activity. Specifically, the mean acceleration value of walking ( $12.4 \text{ m/s}^2$ ) is typically about 27 times higher than the mean acceleration of other activities (0 to  $0.9 \text{ m/s}^2$ ). Thus, it is highly distinguishable (Shin, 2012) and enables an easy detection of walking as an activity.

The minimum walking acceleration value is determined empirically based on previous observations. The instantaneous phone acceleration values during walking ranges from 0 to approximately  $30 \text{ m/s}^2$ , with the temporal average of 98% being above  $10 \text{ m/s}^2$ . These values are primarily caused by the movement of the phone when in the pocket, bag, or jacket of the user – they do not correspond strictly to the continuous velocity or acceleration of the person. In contrast, the observed instantaneous phone acceleration value when the user is in a vehicle is typically lower than  $1 \text{ m/s}^2$ . Therefore, after experimentation we determined  $7 \text{ m/s}^2$  as the minimum average walking acceleration value for walking start/stop detection (i.e., during walking no average acceleration value is lesser than  $7 \text{ m/s}^2$ ). It is worth noting that our temporal averaging of the acceleration values will classify slightly discontinuous walking as a walking activity.

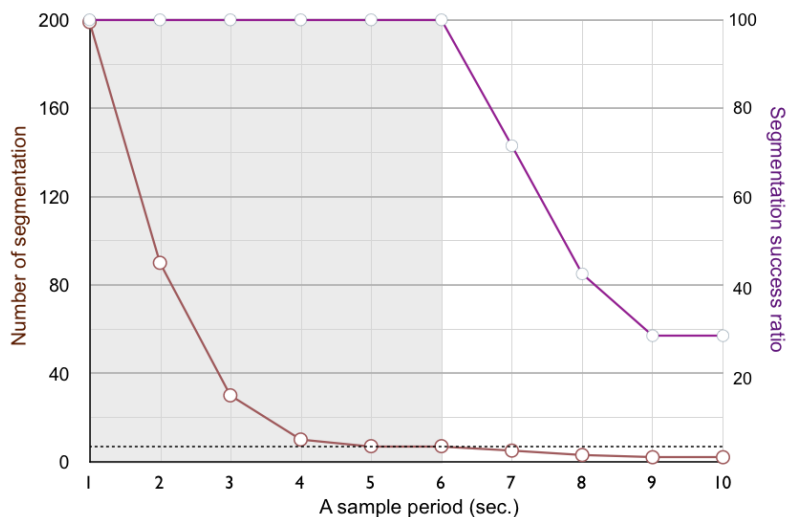


**Fig. 3. Example of acceleration signal.** In this example one-hour acceleration signal, the mobile phone user progressed through multiple daily activities and transportation modes.

Once a walking interval is detected, it can then be utilized as a separator that marks the start and end of an in-between activity. For instance, when riding a car, one has to previously walk to a car and afterwards walk away from the car. A similar process occurs when taking the bus; e.g., one walks to the bus stop, gets on the bus, and afterwards gets off the bus. Hence, every vehicle riding activity is always surrounded by a pair of walking activities.

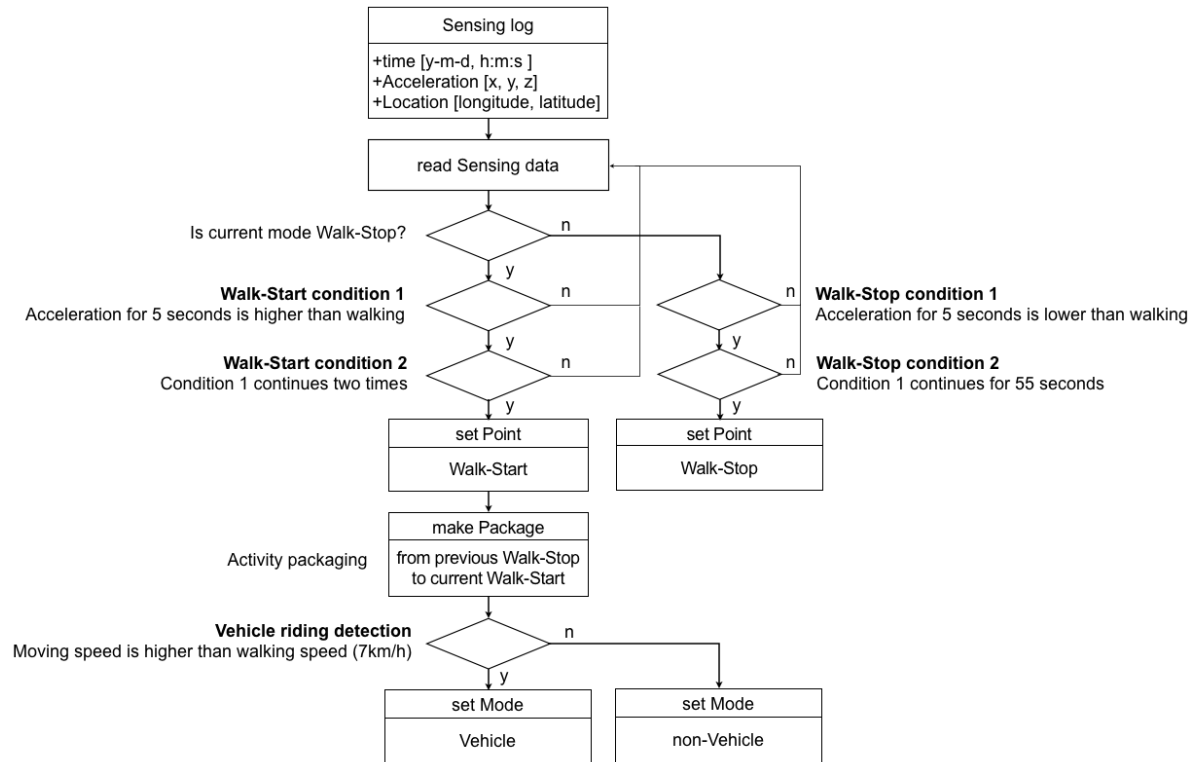
#### 4.2 Activity segmentation and classification

Once the activities are separated, using walking as a separator, a bundle of activity segments can be created from the logged data and the transportation mode assigned to each activity segment. An activity segment is classified as ‘vehicle-riding’ if its average acceleration value is less than the observed minimum walking acceleration value; else it is considered a walking activity. Fig. 4 shows the experimental results of the accuracy changes for different sampling periods. It was tested from 1 to 10 seconds. A long sampling period can result in a small number of segments. Moreover, it could miss an important segmentation. A short sampling period is more accurate but can produce unnecessary segments. It indicates 4 to 6 seconds as a reasonable balance between segmentation accuracy and number of segments – we wish to avoid over- or under-segmentation as well as provide high-accuracy. For our later experiments, we choose a sampling period of 5 seconds to compute the average acceleration value.



**Fig. 4. Number of segments by different sampling periods**





**Fig. 5. Flow chart.** A diagrammatic summary of the transportation mode detection algorithm.

The process of activity segmentation and classification is done using four separate algorithms. These algorithms are summarized in Fig. 5 and are explained in the following four subsections.

### Walk start detection

The first algorithm of transportation mode detection is finding the start of a walking activity. There are two necessary conditions for the algorithm to confirm a point as the start of a walking activity:

- the first condition is finding an average acceleration value greater than or equal to the minimum walking acceleration ( $7 \text{ m/s}^2$ ), and
- the second condition is satisfying the first condition for at least another 10 seconds.

These conditions aim to filter out non-walking accelerations and, while not perfect, in practice we observe significant accuracy, as will be shown later in the article.

### Walk stop detection

The second algorithm of transportation mode detection is recognizing a stop in walking. Defining a stop walking point also has two necessary conditions:

- the first condition is finding an interval when five seconds of average acceleration is lower than the minimum walking acceleration, and
- the second condition is satisfying the first condition for at least another 55 continuous seconds (e.g., the typical minimum train/bus travel time between two consecutive stops in the city of Zurich).

The necessary conditions (of start and stop walking) help to avoid unnecessary walking activity detection, such as when waiting for a crossing signal or idle time during a genuine walking activity. In other words, the algorithm only determines a walk stop point when a user really stops walking more than 55 seconds contiguously (e.g., rides on a bus and travels at least one bus stop station

without walking). Otherwise, it is considered that the walking activity is continued or vehicle riding activity has not been started. The value of 55 seconds has been selected as the typical minimum time for a public transportation bus or train in city Zürich and suburbs in Switzerland to travel between two stops. This value has been derived from an analysis of public transportation schedules and timetables. We set the minimum value in order to include all the cases. For example, bus line A has 28 stops and the total travel time is 25 minutes at 11 PM. The time for one stop is obtained by averaging several such transportation lines, obtaining approximately 55 seconds between stops. Clearly, the minimum travel time for filtering walk stop detection is city dependent.

### **Activity packaging**

Once we detect start/stop walking, the next step is activity packaging. An activity segment is defined in between each corresponding pair of adjacent stop and start walking points. We use the assumption that during any one-activity segment, only one transportation mode is adopted. The aforementioned filtering of small walking activities and the conditions for start/stop walking help to reduce the amount of unnecessary activity segments. It is worth noting that if a segment of large acceleration is converted to an activity segment, it can still be classified as walking (by means of not fitting into any travel mode). Thus, over-segmentation into activity segments is not necessarily harmful.

### **Vehicle riding detection**

The following algorithm for transportation mode detection classifies the activity as either vehicle riding or not vehicle riding. We used average speed. This classification is calculated by using the displaced distance that is measured by network-based location data and the duration of the activity segment. If the average speed is greater than 95% of the highest walking speed (i.e., 7km/h as per (Ashburner et al., 2011)) then the activity is determined a vehicle riding activity. Altogether, the aforementioned algorithms enable extracting walking or vehicle-riding activity segments from sensor data and can be used for a more in-depth analysis within selected activities.

## **4.3 Sample cleaning**

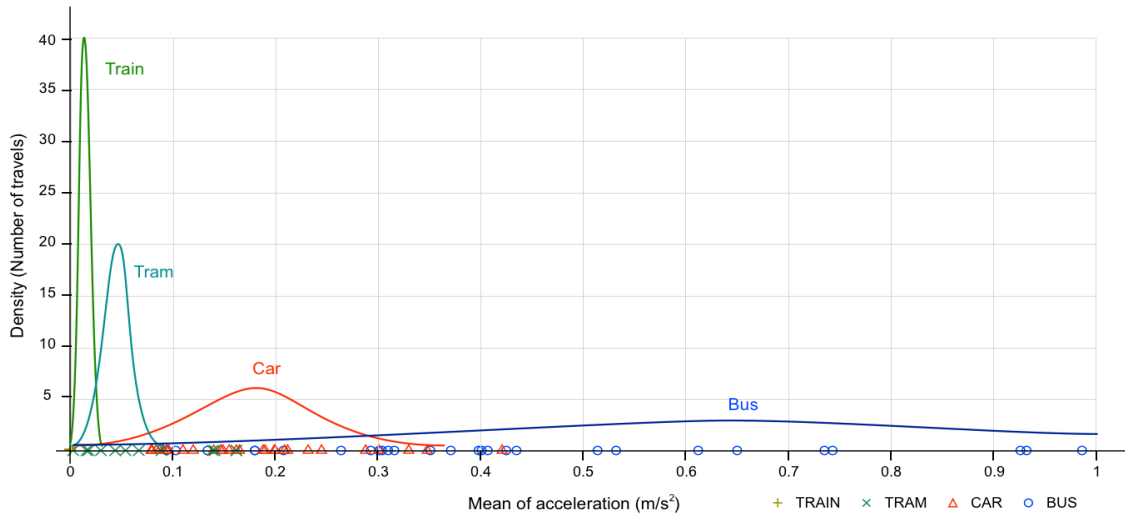
The activity classifying method described in this article mainly relies on sampling acceleration values. It requires extracting pure acceleration samples during travel. Therefore we implemented the following sample cleaning methods:

- Pure vehicle riding data extraction: When the individual uses public transportation there are sequential behaviours (e.g. people wait for a bus by standing or strolling, people walk into a bus when a bus arrives, and people walk off the bus when they arrive at the destination). Therefore, from the first moment the stop-walking activity is detected, we ignore samples until the location changes sufficiently. The tolerance of the location change value follows the 95% of the highest walking speed (i.e., 7km/h as per (Ashburner et al., 2011)).
- Filtering sudden walking in a vehicle: Passengers may walk while in a vehicle, such as a train or bus. Thus, we filter short walk sequences that may occur inside a vehicle activity segment.

## **4.4 Travel Mode Detection**

To determine the travel mode of a vehicle-ride activity, we estimate an acceleration profile for each mode and use it to classify particular acceleration behaviour into one of the recognized travel modes. In our application, we support trains, buses, and cars. While their acceleration profiles are not guaranteed to be disjoint, we have found in practice relatively well-separated behaviour –

considering we already know that we are on a vehicle. As per Section 3.2, we only need to determine which mode of transportation. Thus, during a calibration run of our application, we capture several datasets of acceleration readings for each travel mode and fit a Gaussian distribution curve to each. Therefore we can recognize the travel mode by matching the predefined acceleration profiles.

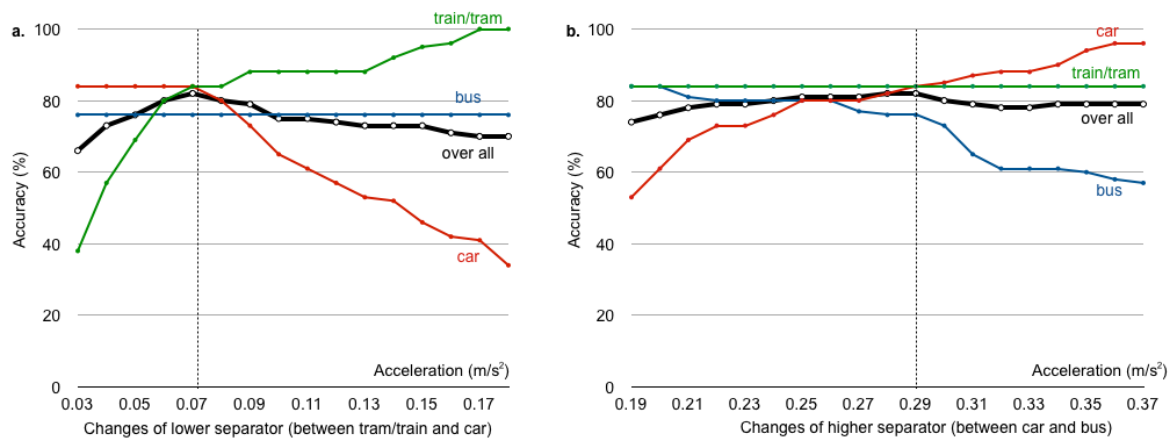


**Fig. 6. Acceleration distribution on different vehicles.** It shows the distribution of each vehicle’s mean acceleration value.

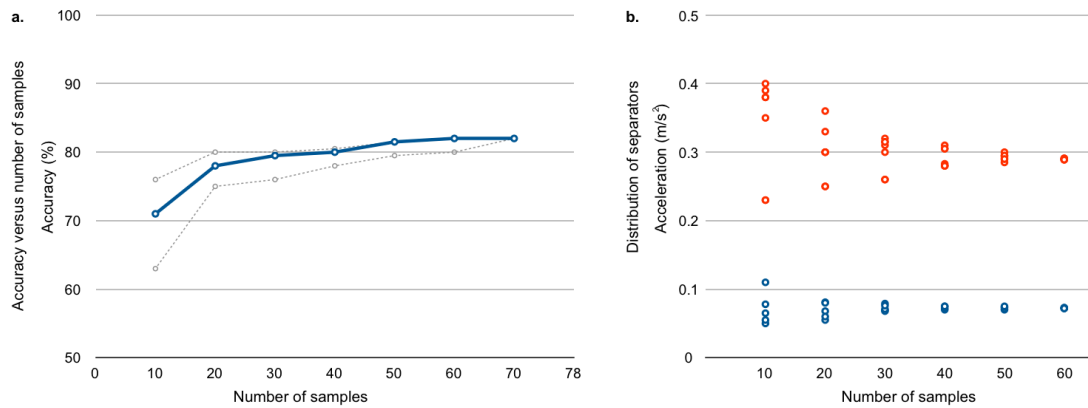
Fig. 6 presents the Gaussian distribution curves that correspond to the acceleration level of each travel mode (i.e., train, tram, car, and bus) obtained during the calibration run of 78 datasets in Zürich (Shin, 2012). In this graph, we show trams (e.g., small in-town trains) and regional trains separately, but we classify them collectively as train/tram.

The green line represents the acceleration distribution of (regional) trains, which has the lowest acceleration of all. The tram has a slightly higher acceleration level than the (regional) train, but still has a very low level of acceleration. The blue curve represents the bus’s acceleration level, and the car’s acceleration is between the train and the tram. Based on this clustered distribution of each vehicle’s acceleration, we defined the two separation values to classify different vehicle types.

Fig. 7 shows the trend how the accuracy is changed by shifting the separation value. For instance, if the separation value 0.290 in Fig. 7b is shifted to the lower one 0.250, then the vehicle classified as a car between the values 0.25 and 0.29 will be classified as bus. This will increase the accuracy of bus detection since it has wider range, however it will decrease car detection accuracy. Therefore, the thresholds are chosen to maximize the overall accuracy using our calibration runs: train/tram = [0, 0.072], car = [0.072, 0.290], and bus = [0.290, 1.0].



**Fig. 7. Changes of classification accuracy (%) versus changes of separation values.** a) The accuracy trends when the lower separator (0.072) is changed (The higher separation value is fixed in 0.290.), b) The accuracy trends when the higher separator (0.290) is changed (The lower separation value is fixed in 0.072.)



**Fig. 8. Cross validation (accuracy vs. altering number of samples).** a) Accuracy (%) versus number of samples. b) Separator distribution by random sample selection.

In order to see the credibility versus different number of samples, we measure the accuracy 10 to 70 samples by 10-sample steps. Each step has five different random samples generating separators and we compare the accuracy with the rest of samples, which have a ground truth data. Fig 8. shows accuracy versus changes in the number of samples. It reached the 98% of maximum accuracy with 40 samples. This result shows that we can calibrate the separator values if we have more than around 40 samples. In this research we obtain 495 segmented sample sets in Zurich. For the fine calibration, we collectively select 78 sample sets (30 users), which include ground truth data. In this measurement, we used simple random sampling. Random sampling eliminates bias by giving all individuals an equal opportunity to be chosen (Moore & McCabe, 1989) in urban legend and this identification algorithm is not related to population characteristics but to acceleration, therefore simple random sample is our solution.

In order to compare acceleration concentrations subjected to transportation mode, we performed analysis of variance (ANOVA) and t-tests. Differences in concentrations of acceleration were observed by different modes. Results indicate vehicle acceleration changes of bus are significantly larger, while those of train are relatively smaller than other modes with statistical significance. ANOVA and t-tests with multiple comparisons reveal that all three groups have different acceleration rates at the 1% level of significance (Table 1, 2). These tests verify our solution for

vehicle classification uses statistically significant thresholds. All descriptive computations and statistical analyses were made using SAS software (version 9.2).

	DF	SS	MS	F-Value	p-value
<b>Between Group</b>	2	2.148	1.074	43.2	***
<b>Within Group</b>	75	1.864	0.025		
<b>Corrected Total</b>	77	4.012			

Significance level: \*<.10, \*\*<.05, \*\*\*<.01

**Table 1. Results of One-way ANOVA**

	Mode (A)	Mode (B)	Mean Difference (A-B)	CI (99%)	p-value
Turkey	bus	car	0.258	0.127 0.390	***
	bus	train/tram	0.401	0.270 0.532	***
	car	train/tram	0.143	0.011 0.274	***
Bonferroni	bus	car	0.258	0.126 0.391	***
	bus	train/tram	0.401	0.268 0.534	***
	car	train/tram	0.143	0.010 0.275	***
Scheffe	bus	car	0.258	0.121 0.395	***
	bus	train/tram	0.410	0.264 0.538	***
	car	train/tram	0.143	0.006 0.280	***

Significance level: \*<.10, \*\*<.05, \*\*\*<.01

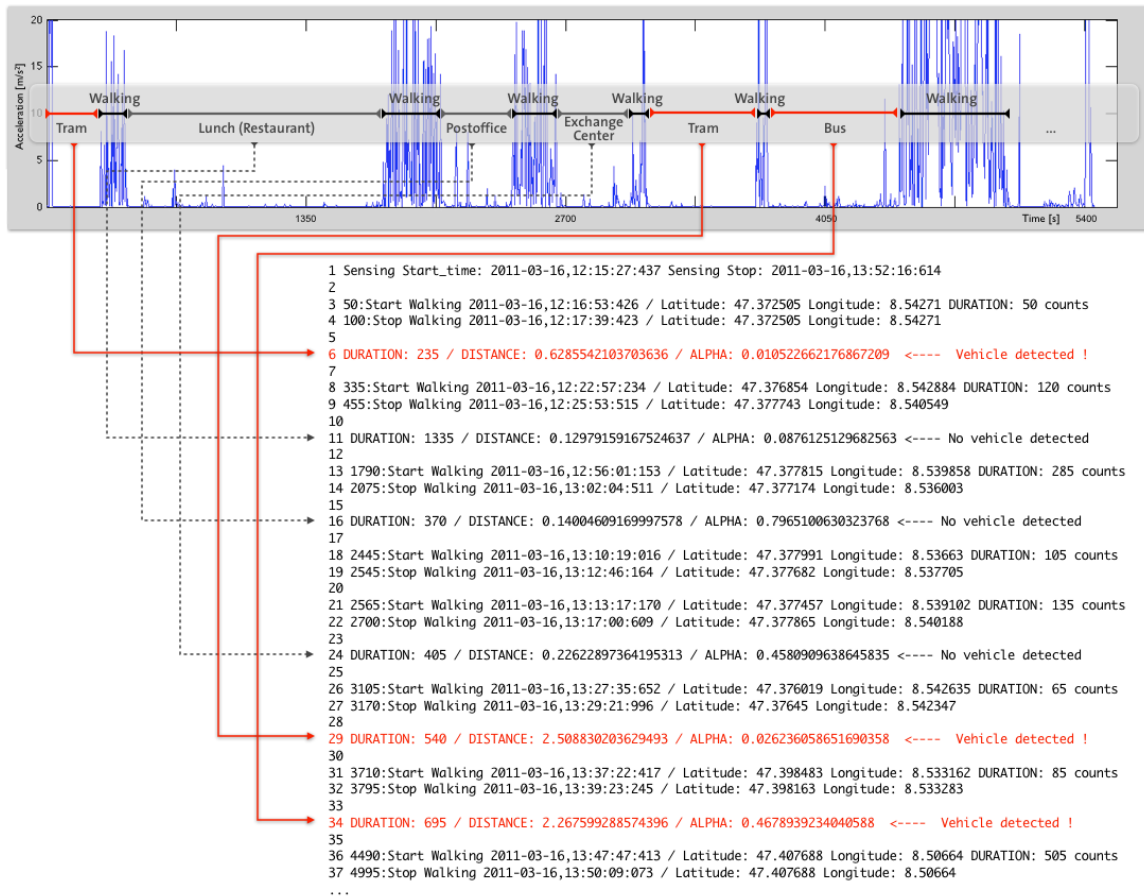
**Table 2. Multiple Comparisons between Different Modes (t-test)**

## 5. Evaluation results

We have performed several deployments and accuracy evaluations of our application. The following figures are based on comparing the results of our method to ground truth using data collected by 30 users. Users noted their activities every time they got on and off a vehicle, and also when they did a non-vehicle activity. This annotated log enabled us to create the ground-truth for each dataset. The recorded activity was within Zürich, and made use of the local trains, tram, buses, walkways, and private cars.

User No.	Starting points	Destinations	Time	Ground truth	Classified as	Acceleration	Verification
1	Halmhaus	Bucheggplatz	15:19	tram	tram	0.162	TRUE
	Bucheggplatz	ETH hoenggerberg	15:40	bus	bus	0.986	TRUE
2	ETH Universitatsspital	Bucheggplatz	9:52	tram	tram	0.018	TRUE
	Bucheggplatz	ETH hoenggerberg	10:02	bus	bus	0.735	TRUE
3	ETH hoenggerberg	Meirhofplatz	15:00	bus	bus	0.371	TRUE
	Meirhofplatz	Escher-Wyss-Platz	15:05	tram	tram	0.003	TRUE
	Escher-Wyss-Platz	Silcity Nord	15:17	bus	bus	0.926	TRUE
4	Glaubtenstr.	Oerlikon	14:06	bus	car	0.103	FAIL
	Oerlikon	Dietlikon	14:29	train	train	0.032	TRUE
	Dietlikon	Zurich HB	15:45	train	train	0.011	TRUE
5	ETH hoenggerberg	Meierhofplatz	13:46	bus	bus	0.351	TRUE
	Meierhofplatz	Zurich HB	13:59	tram	tram	0.067	TRUE
	Holzerhurd	Kernstrasse	18:21	bus	bus	0.532	TRUE
7	Werd	Neuauffoltern	18:22	car	car	0.084	TRUE
	Einfangstrasse	Flughafen	16:27	car	bus	0.301	FAIL
	Zurich HB	Limatplatz	16:31	tram	tram	0.044	TRUE
	Limatplatz	Lagerstrasse	18:40	bus	bus	0.407	TRUE
8	Galubtenstr.	Escher-Wyss-Platz	8:30	bus	bus	0.293	TRUE
	Lauffohr, Dorf	Untersiggenthal, Hölzli	18:46	car	car	0.288	TRUE
9	Untersiggenthal, Hölzli	Lauffohr, Sommerhaldenstrasse	19:01	car	car	0.096	TRUE
...	...	...	...	...	...	...	...

**Table 3. Accuracy of our transportation mode detection algorithm.** The algorithm was evaluated by using ground truth data. Our method achieved, on average, 82.05% accuracy.



**Fig. 9. An example of half hour acceleration signal and output data from the detecting algorithm.**

Fig. 9 shows detailed results from our transportation mode detection algorithm for one example dataset. The detection output shows 6 segmentations (except for walking) are classified and three

segmentations among them are identifies to vehicle ridings. The graph at the top plots the acceleration values during multiple activities. The ground truth activities indicated by the user have been overlaid on the graph. Unlabelled regions correspond to walking. The text below the graph is a verbose output of the Java application implementing the vehicle mode detection algorithm. The application detected six non-walking activities (line no. 6, 11, 16, 24, 29, 34) and these six activities correspond correctly with the ground truth activities (i.e., 100% accuracy). Furthermore, when factoring in moving distance, the three activities (i.e., line no. 6, 29, 34) were recognized as vehicle riding activities. Travel mode detection is not shown here – will be in a later figure. As can be seen, despite the variety of activities, our algorithm is able to correctly classify the transportation mode of the smartphone user, without hindering on the person’s activities.

We present the accuracy of the transportation detection algorithm in Table 3. We compare the ground-truth values to our algorithmically computed values in order to compute the accuracy values for each user. For the column labelled ‘Verification’, we count the total number of matches, and divide by the total number of samples for the dataset. Our overall accuracy is 82.051%.

Ground truth	Classified as			
	Walk	Train/Tram	Car	Bus
Walk	100%	0.00%	0.00%	0.00%
Train/Tram	0.00%	88.46%	11.54%	0.00%
Car	0.00%	3.85%	80.77%	15.38%
Bus	0.00%	3.85%	19.23%	76.92%

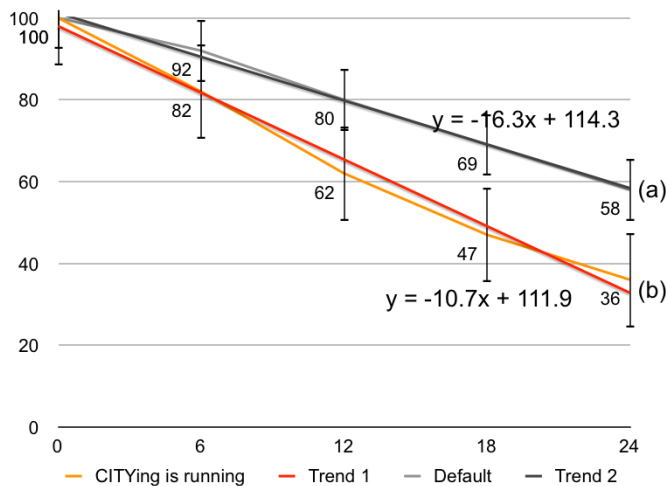
**Table 4.** Accuracy matrix for travel type detection.

In Table 4, we evaluate our additional algorithm for detecting the travel mode. The left column lists ground truth data, which comes from the user. The top row indicates the supported travel modes. The table shows the accuracy of each activity type and the percentage of misclassifications. The activities, Walk and Tram/Train, are classified as high accuracy with above 88%, while Car and Bus have 76-80% accuracy and 15-19% of misclassification.

Implementing a battery-optimized application is challenging work for an application that should run for a long time and using phone sensors. Even though mobile phone companies keep improving battery capacity, many recent surveys (Ferreira et al., 2011 Carroll et al., 2010) still indicate that the most common complaint of smartphone users is poor battery life. Thus, we seriously considered battery efficiency from the initial moment of the research and we adopted the following aspects to optimize it.

- high-efficiency activity classification - our program makes activity segments with separators (i.e., walking signal) first and then selectively performs in-depth travel mode analysis;
- low sampling rate - we experimentally determined that a sampling interval of 1 second is sufficient; and
- non-GPS technology used in location sensing - we use network-based location sensing technology which is practical to use in most indoor/outdoor locations and weather conditions.

Fig. 10 shows the actual amount of the battery consumption. Normal usage, (a) of Fig. 10, implies basic use, including network use, default Android data synchronizing service enabled, 3G network service, Wi-Fi, a messenger application, a Google email application, and default media sync functions. The horizontal axis corresponds to hours of continual use and the vertical access to percent of battery power remaining.:



**Fig. 10. Battery efficiency of CITYing.** The figure shows (a) the average battery consumption in normal usage and (b) battery consumption when the CITYing is running continuously under normal usage.

## 6. Conclusions and future work

We have presented a method for urban data collection, sensing and classifying of diverse transportation activities using smart phone sensors. Our automatic method performs transportation mode classification at the urban scale and runs on today's smartphones. Our solution is concerned with high battery-life efficiency but without losing accuracy and without disturbing user's daily mobile phone use -- since mass participation is necessary to form our large-scale crowdsourcing environment. In this context, our low sampling rate, network based location sensing, and robust detection algorithm are implemented and experimented, yielding high accuracy results.

Our algorithm exploits that walking has significantly different acceleration levels as compared to other transportation modes and every vehicle-riding activity is always surrounded by walking. We implemented a walking detection algorithm, a vehicle activity packaging procedure, and a travel mode classification method. Finally, we provide a Java-based Android smart phone application implementing the entire approach. Also, it is able to filter out noisy readings with minimal effort and has very large tolerance in location accuracy (i.e., does not need GPS readings) -- it doesn't rely on the precise location sensing, so it is practical to use in most indoor/outdoor locations and weather conditions.

Our approach is not without limitations. Our activity classification is based on a case study of Zurich and immediate suburbs in Switzerland. Currently, we are extending experimentation to other cities: Singapore, London, and Seoul. Not all travel modes, in all cities, can necessarily be classified with our approach. Therefore, our future plan includes extending the case study into other cities with potentially other travel modes.

**Future work.** There are several avenues of future work. First, we are developing a user-friendly application which will provide intuitive visualizations of long term user activities. Since all the data is rooted in individual activities, the information can help people realize the outcome of their transportation decisions and activities. This is a very important aspect of this research, since it can lead to a real sustainable urban environment by raising awareness. This educational effect will hopefully lead to people changing their behaviour to the benefit of the environment.

Second, we would like to integrate semantic notions into the classification scheme. This semantic information can help to improve classification accuracy (e.g., by recognizing home and work



location (Calabrese et al., 2013) and knowing the route that is most likely taken each day) and further analysis. Semantic and more in-depth analysis can also create more sophisticated patterns of behaviour that can be applied to social sensing applications. For instance, "Google Now" delivers information based on the user's location and requirements. It could notify the user of traffic, provide a train schedule or favourite sports team's score. Such an application works based on location and time. However if we can append semantic user data (e.g. detected travel mode and activity sequence) to the location and time data, we can deduce probable user activities and provide more related information on a need to know basis.

## 7. References

- Adams, B., D. Phung, et al. (2008). "Sensing and using social context." *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMCCAP)* 5(2): 11.
- Allio, R. J. (2010). "CEO interview: the InnoCentive model of open innovation." *Strategy & Leadership* 32(4): 4-9.
- Alt, F., A. S. Shirazi, et al. (2010). Location-based crowdsourcing: extending crowdsourcing to the real world, ACM.
- Asakura, Y., Hato, E. (2005) Tracking survey for individual travel behaviour using mobile communication instruments. *Transportation Research Part C* 12, 2730291.
- Ashburner, J. M., J. A. Cauley, et al. (2011). "Self-ratings of Health and Change in Walking Speed Over 2 Years: Results From the Caregiver-Study of Osteoporotic Fractures." *American Journal of Epidemiology* 173(8): 882.
- Barbeau, S. (2011). "Participatory Sensing: Smart Phones as Sensors in a Connected World." Presented at Transportation Research Board (TRB) P11, 1654.
- Becker, R., R. Caceres, et al. (2013). "Human mobility characterization from cellular network data." *Communications of the ACM* 56(1): 74-82.
- Bell, K. E., S. M. Kothuri, et al. (2013). "Emission model sensitivity analysis: The value of smart phone weight-mile tax truck data."
- Berlingerio, M., F. Calabrese, et al. (2013). AllAboard: a system for exploring urban mobility and optimizing public transport using cellphone data. *Machine Learning and Knowledge Discovery in Databases, Springer*: 663-666.
- Bolbol, A., Cheng, T., Tsapakis, I., Haworth, J. (2012) Inferring hybrid transportation modes from sparse GPS data using a moving window SVM classification. *Computers, Environment and Urban Systems* 36, 526-537.
- Calabrese, F., M. Diao, et al. (2013). "Understanding individual mobility patterns from urban sensing data: A mobile phone trace example." *Transportation research part C: emerging technologies* 26: 301-313.
- Campbell, A. T., S. B. Eisenman, et al. (2006). People-centric urban sensing. *Proceedings of the 2nd annual international workshop on Wireless internet, ACM*.
- Carroll, A. and G. Heiser (2010). An analysis of power consumption in a smartphone. *Proceedings of the 2010 USENIX conference on USENIX annual technical conference*.

- Cohen, J. (1992). "Statistical power analysis." *Current directions in psychological science* 1(3): 98-101.
- Cuff, D., M. Hansen, et al. (2008). "Urban sensing: out of the woods." *Communications of the ACM* 51(3): 24-33.
- Demirbas, M., M. A. Bayir, et al. (2010). Crowd-sourced sensing and collaboration using twitter. *World of Wireless Mobile and Multimedia Networks (WoWMoM), 2010 IEEE International Symposium on a, IEEE.*
- Ferreira, D., A. K. Dey, et al. (2011). Understanding human-smartphone concerns: a study of battery life. *Pervasive Computing, Springer:* 19-33.
- Fingler, J., D. Schwartz, et al. (2007). "Mobility and transverse flow visualization using phase variance contrast with spectral domain optical coherence tomography." *Optics express* 15(20): 12636-12653.
- Finin, T., W. Murnane, et al. (2010). Annotating named entities in twitter data with crowdsourcing, *Association for Computational Linguistics.*
- Freire, M. and R. E. Stren (2001). *The challenge of urban government: policies and practices*, World Bank Publications.
- Gonzalez-Feliu, J., Pluvinet, P., Serouge, M., Gardrat, M. (2013), Urban Freight Analysis Based on GPS Data. In Hsueh, Y.H. (ed.), *Global Positioning Systems: Signal Structure, Applications and Sources of Error and Biases*, Nova Science Publishers, pp. 73-93.
- Gould, J. (2013). "Cell Phone Enabled Travel Surveys: The Medium Moves the Message." *Transport Survey Methods: Best Practice for Decision Making:* 51.
- Graham, S. (1997). "Cities in the real-time age: the paradigm challenge of telecommunications to the conception and planning of urban space." *Environment and Planning A* 29: 105-128.
- Hemminki, S., P. Nurmi, et al. (2013). Accelerometer-based transportation mode detection on smartphones. *Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems, ACM.*
- Jansen, J. L. G. (2011). "Developing an application in Google Android to support autonomous living of people with cognitive disabilities." *POLITECNICO DI MILANO.*
- Joki, A., J. A. Burke, et al. (2007). "Campaignr: a framework for participatory data collection on mobile phones." *Papers, Center for Embedded Network Sensing, UCLA.*
- Kaltenbrunner, A., R. Meza, et al. (2010). "Urban cycles and mobility patterns: Exploring and predicting trends in a bicycle-based public transport system." *Pervasive and Mobile Computing* 6(4): 455-466.
- Kessler, D. and P. Temin (2007). "The organization of the grain trade in the early Roman Empire." *The Economic History Review* 60(2): 313-332.
- Kim, S. A., D. Shin, et al. (2012). "Integrated energy monitoring and visualization system for Smart Green City development: Designing a spatial information integrated energy monitoring model in the context of massive data management on a web based platform." *Automation in Construction* 22: 51-59.
- Krasner, N. F. (2010). A GPS receiver and method for processing GPS signals, EP Patent 1,260,830.
- Madan, A., M. Cebrian, et al. (2010). Social sensing for epidemiological behavior change, *ACM.*
- Miller, H. J. (1999). "Potential contributions of spatial analysis to geographic information systems for

transportation (GIS-T)." *Geographical Analysis* 31(4): 373-399.

Miller, H. J. (2013). "Beyond sharing: cultivating cooperative transportation systems through geographic information science." *Journal of Transport Geography*.

Moore, D. S. and G. P. McCabe (1989). *Introduction to the Practice of Statistics*, WH Freeman/Times Books/Henry Holt & Co.

Murty, R., A. Gosain, et al. (2008). *Citysense: A vision for an urban-scale wireless networking testbed*, Citeseer.

Paek, J., J. Kim, et al. (2010). *Energy-efficient rate-adaptive gps-based positioning for smartphones*, ACM.

Pluvinet, P., J. Gonzalez-Feliu, Ambrosini, C. (2012). "GPS data analysis for understanding urban goods movement." *Procedia-Social and Behavioral Sciences*, vol 39, pp. 450-462.

Reades, J., F. Calabrese, et al. (2007). "Cellular census: Explorations in urban data collection." *Pervasive Computing*, IEEE 6(3): 30-38.

Santos, A. C., J. M. P. Cardoso, et al. (2010). "Providing user context for mobile and social networking applications." *Pervasive and Mobile Computing* 6(3): 324-341.

Shin, D., S. M. Arisona, et al. (2012). "A Crowdsourcing Urban Simulation Platform on Smartphone Technology: Strategies for Urban Data Visualization and Transportation Mode Detection." *Digital Physicality - Proceedings of the 30th eCAADe Conference - Volume 2 / ISBN 978-9-4912070-3-7*, Czech Technical University in Prague, Faculty of Architecture (Czech Republic) 12-14 September 2012, pp. 377-384.

Turner, H., J. White, et al. (2011). "Engineering Challenges of Deploying Crowd-based Data Collection Tasks to End-User Controlled Smartphones." *3rd International Conference on Mobile Lightweight Wireless Systems*.

Vasileios, Z., M. George, et al. (2010). "Indoor Positioning Using GPS Revisited." *Pervasive Computing*: 38-56.

Wang, H., Calabrese, F., Di Lorenzo, G., Ratti, C. (2010) *Transportation mode inference from anonymized and aggregated mobile phone call detail records*. 13th International IEEE Conference.