# A Crowdsourcing Urban Simulation Platform on Smartphone Technology

## *Strategies for urban data visualization and transportation mode detection*

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**Abstract.** *We propose a crowdsourcing simulation environment that brings human intention into the urban simulator. Our fundamental goal is to simulate urban sustainability by employing direct human interaction. In this paper we present a prototype mobile phone application that implements a novel transportation mode detection algorithm. The mobile phone application runs in the background and continuously collects data from the built-in acceleration and network location sensors. The collected data is analyzed by the transportation mode detection algorithm and automatically partitioned into activity segments. A key observation of our work is that walking activity can be robustly detected in the data stream and acts as a separator for partitioning the data stream into other activity segments. Each vehicle activity segment is then sub-classified according to the type of used vehicle. Our approach yields high accuracy despite the low sampling interval and not requiring GPS data that bring minimized device power consumption. Ultimately, the collected information can be translated into real-time urban behavior and will indicate sustainability, both on the personal and the city level.*
**Keywords.** *Crowdsourcing simulation platform; transport mode detection; social sensing; urban sustainability; mobile application.*

## INTRODUCTION

The research area of urban simulation methods has grown notably in recent decades. Most of the research topics that concern urban simulation are concentrated on defining the complexities of urban environments (Delaney, 2000). However, cities are getting more complex and changes in them take place at greater speed. In this context, research is necessary to develop fundamental simulation methods that can handle these complexities and dynamics as design decision support systems in addition to existing methodologies. For future urban development, stakeholders, urban designers and governments shall require the advanced methods or tools, which can deal with these extreme urban complexities.

In order to successfully develop new methodologies and techniques it is necessary to answer the following questions: What are the origins of the complexities and transformations of the urban environment? How can we approach these origins in order to deal with the urban complexities and transformations in the most efficient manner? We hypothesize that the diverse human intentions and activities are the origin of the complexities and changes of the cities. In this context, we propose a crowdsourcing (Howe, 2006) simulation environment that is operated on people's smartphone and registers their everyday movements around the city. The recent wave of sensor-rich, internet-enabled, and smart mobile devices such as the Apple iPhone and Google Android phone has opened the door for implementing the real urban environment into the simulation environment known as participatory sensing. We claim that the direct participation of citizens induces a paradigm shift from rule-based simulation to human-agent based simulation and will help to cope with urban complexity within the simulation. This crowdsourcing simulation environment will enhance the accuracy of the simulation and solve the complex problems in fundamental ways by reflecting human intention and social trend directly.

[Figure 1] shows the concept of the proposed crowdsourcing simulation platform, in which humans drive the simulation instead of virtual agents that react to predefined algorithms. People can participate in the simulation with their mobile devices that provide location information, and share related information through social networks such as Facebook, Twitter, and Youtube.

## RESEARCH OBJECTIVES

The research fundamentally aims at involving public participation in order to reflect people's intentions and daily travels in urban areas. In this context, this research consists of the following four processes [Figure2]: i. definition of a behaviour detection algorithm; ii. mobile application distribution; iii. data collection and analysis; iv. visualization of urban activities and simulation of future cities.

At this stage, the algorithm classifying the behaviour pattern is being developed and implemented in a mobile application. As further steps, the application will be released to the public through diverse social network services. The collected data will be translated into information and give a benefit to the user by analysing user information and creating a so-called "life pattern". The retrieved data from the public will be analysed and simulated in urban scale for the development of future urban environments. At the final stage, the analysed data will be utilized in a feedback loop, thus constantly upgrading the crowdsourcing simulation environment.

In this paper, we focused on sensing and classifying human behaviour. In particular, we present the experimental results on detecting transportation activity using a mobile sensor. Based on these results, the entire sensing and data acquisition procedure will be automated. Users do not need to spend time to input specific information since this will be done by sensors. However, the information will be returned and displayed to the citizens, enhancing their energy-aware life.

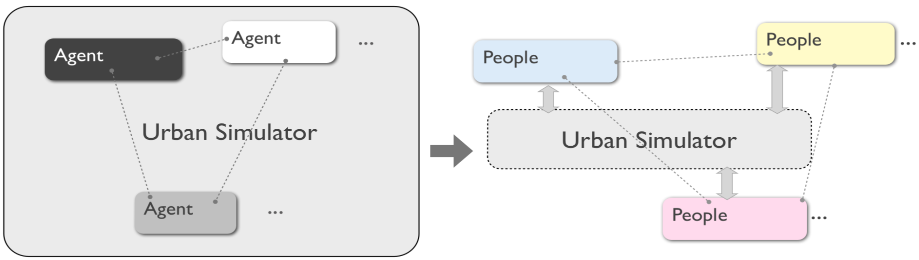
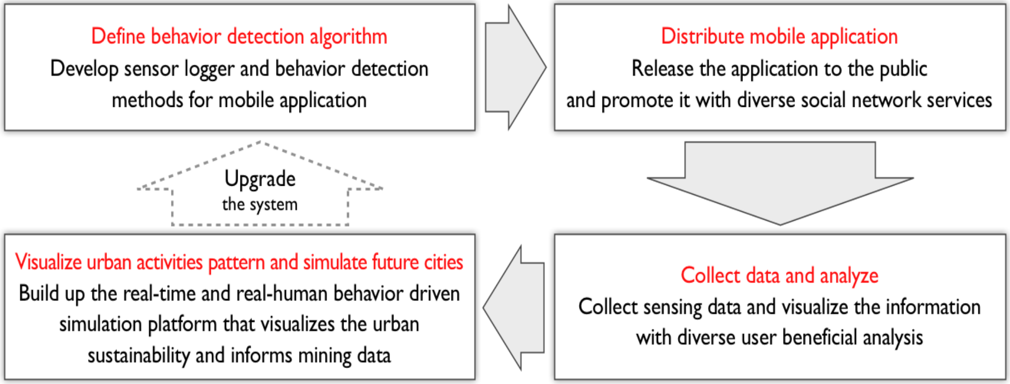



*Figure 1*
*Paradigm shift of an urban simulation design from MAS (Multi-agent simulation) to CMAS (Crowdsourcing multi-agent simulation).*

Figure 2
*The overall proposed procedural process in terms of research method: Implementation, distribution, execution, and analysis. Behavior and travel sensing algorithm will be implemented and released to public use.*




## CURRENT STATE OF RESEARCH IN THE FIELD

Before modern crowdsourcing systems were introduced, there were a number of notable examples of projects that utilized distributed people to help accomplish tasks. The Oxford English Dictionary may provide one of the earliest examples of crowdsourcing. An open call was made to the community for contributions by volunteers to index all words in the English language and provide quotations for each and every one of their usages (Brown, 1993). Crowdsourcing has often been used in the past as a competition in order to discover a solution. The French government proposed several of these competitions, often rewarded with Montyon Prizes (Crosland, 1979), created for poor Frenchmen who had done virtuous acts. Today, under the umbrella of crowdsourcing, there are several types of human resources that can be used depending on the project. Wikipedia (http://www.wikipedia.org/) is one example, in which all over the world hundreds of thousands of volunteers contribute information on almost 21 million topics in order to create complete articles. Currently Wikipedia has become the biggest encyclopedia in the world. Research and development provides many opportunities for crowdsourcing people's thoughts and ideas. The company InnoCentive is a crowdsourcing platform for corporate research and development, where difficult scientific problems are posted for crowds of solvers to discover the answer (Allio, 2010). Harvard Tuberculosis Lab teamed with CrowdFlower to help identify drug resistant TB cells in mouse cortex slides. If they had not used crowdsourcing, the project would have been stalled considerably due to lack of manpower to investigate at all the images (Finin, 2010).

Smart phones offer researchers the possibility to develop applications that collect information from an extensive number of individuals and in this way to study the dynamics of large populations. Many research efforts and developments are emerging that utilize and implement "crowdsourcing" – i.e., collecting large amounts of data from individual users via smartphones (Joki et al., 2007, Murty et al., 2008, Turner et al., 2011). Moreover, smartphone-based data collection is becoming increasingly important to planning agencies and private firms (Alt, 2010). However, mobile crowdsourcing has not yet been established as a widespread medium for data collection, because most of the existing applications require active user input, and as users 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 (Madan et al., 2010, Adams et al., 2008). It is possible to use the sensors and stochastic algorithms of a smartphone in order to automatically detect certain types of user activity. In this section, we provide an outline of related research efforts and projects. CO2GO, an on-going project at SENSEable City Lab of MIT, is a smartphone application that aims to sense the transportation mode of users in order to estimate their CO2 emission level (http://senseable.mit.edu/co2go/). Other similar on-going research efforts for detecting the vehicle type in use by an individual, and estimating CO2 emission, include Ecorio (ecorio.org), and Carbon Diem (carbondiem.com). These applications seek to provide alternative path suggestions for reaching the desired destination with lower CO2 emission. They use the smartphone's GPS for collecting location data and the acceleration sensor for transportation mode detection. Using a GPS on a mobile device can quickly drain the battery (Paek et al., 2010). Moreover, GPS only functions outdoors with moderate to good weather conditions (Vasileios et al., 2010) and has limitations in areas with high-rise buildings. In addition, CO2GO, has a fixed sensing rate of 25 times per second, which is very computationally and resource expensive. Therefore, these applications require high accuracy of location data and high frequency of update rate, which consumes a lot of battery power.

In order to deduce meaningful patterns of activities, the applications need to run in the background for a long period of time. Since mobile devices have limited power source (restricted by their battery efficiency), it is hardly possible to collect enough data from one device during an individual's working day. Moreover, power-draining applications are likely to be rejected by the users, as the latter do not want to compromise the use of their telephone 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.

## METHODS AND RESULTS

### *Transportation mode detection*

Currently, we are conducting preliminary studies on defining the behavior detection algorithm. The first goal of behavior detection is transportation mode detection: daily travel distance, vehicle types, and home and working locations. We can therefore measure how much CO2 is emitted from traffic and how much the commute distance and location are optimized in comparison to other cities. [Figure 3] presents our current achievements on the transportation mode detection system, which include acceleration and location data collected by the smartphone's acceleration sensor and data analysis to detect the transportation mode.

The key observation is that the transportation mode of smartphone users can be detected and segmented accurately and efficiently simply by analysing data collected through the built-in acceleration sensor and the network-based location sensor. This way, the transportation mode detector can continuously collect data while the phone is undergoing normal use (e.g., as a background application), and without requiring excessive GPS usage or other auxiliary devices. We are able to improve upon and circumvent GPS's because our goal is not to determine the exact location of the phone user but rather to estimate the mode of transportation based on instantaneous changes in acceleration. In particular, an important finding of our research is that the average smartphone acceleration readings during walking are significantly higher (i.e., 20 times higher) than in other transportation modes. Therefore, walking can be robustly detected and used as a separator between its two adjacent activities, simplifying the segmentation process, and enabling a sub-classification into vehicle types.

Each vehicle activity segment is subsequently sub-classified according to the type of vehicle taken. Our approach yields high accuracy despite the low sampling interval and not requiring GPS data.

The three main steps of transportation mode detection, namely data collection using the acceleration sensors and network-based approximate location, segmentation and classification of the data stream into activity segments, and determination of vehicle type are described in detail in the following sections.

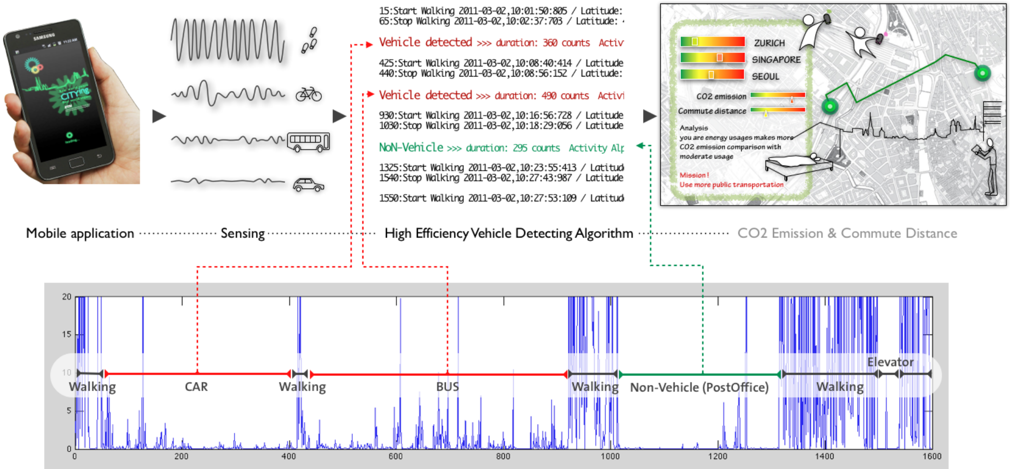



*Figure 3*
*Mobile application implementation: i. acceleration and location data sensing; ii. classification of transportation mode; iii. visualization of travel patterns and sustainability analysis. Preliminary results of parts i. and ii. are already implemented in our study. Part iii. is planned for future development.*

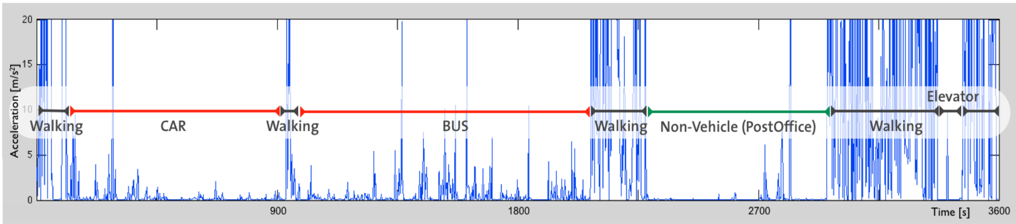



*Figure 4*
*Example acceleration signal. In this exemplary one-hour acceleration signal, the mobile phone user progressed through multiple daily activities and transportation modes. The labeled activities were determined by a manual labeling progress (for this visualization only).*

## *Data collection and analysis*

Our prototype system continually logs three fundamental types of data: i) date and time, ii) x-, y-, and z-acceleration values, and iii) network based location values. The data is stored locally on each phone (in our implementation) and transmitted, in real-time, to a database server using the mobile data network services. The sampling interval is set to 1 second. The total acceleration magnitude is calculated as the Euclidean length of the 3D acceleration vector:

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

The transportation activities we tested include walking, taking the bus, driving the car and taking the train. An example of the first results of this test, covering a period of one hour is presented in [Figure 4]. Upon examination of the logged data, we find that walking can be robustly differentiated from other non-walking activities. Specifically, the average acceleration value of walking is typically about 20 times higher than other activities and thus is highly distinguishable. This enables an easy detection of walking as an activity.

## *Activity segmentation and classification*

Once the activities are separated, a bundle of activity segments can be created from the logged data and 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. The average acceleration value is computed as the mean over a sampling period of 5 seconds. Vehicle activity segments are further sub-classified into vehicle types based on the acceleration behaviour. Although passengers may walk while in a vehicle, such as a train or tram, it is not a dominant activity. Thus, we filter short walk sequences that may occur inside a vehicle activity segment. This also serves to improve the accuracy of estimating the acceleration during non-walking activity and hence vehicle type determination.

### *Vehicle type detection*

To determine the vehicle type of a vehicle-riding activity, we estimate an acceleration profile for each type and use it to classify particular acceleration behaviour into one of the recognized vehicle types. 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 type of vehicle. Thus, during a calibration run of our application, we capture several datasets of acceleration readings for each vehicle type and fit a Gaussian distribution curve to each. Therefore we can recognize the vehicle types by simply matching the predefined acceleration ranges.

[Figure 5] presents the Gaussian distribution curves that correspond to the acceleration level of each vehicle type (i.e., train, car, and bus) obtained during the calibration run of 10 datasets per type. In this graph, we show trams (e.g., small in-town trains) and regional trains separately, but we classify them collectively as trains. The red line represents the acceleration distribution of (regional) trains, which has the lowest acceleration (0 to 0.29 m/s2) of all. The tram (orange) has a slightly higher acceleration level than the (regional) train, but still has a very low level of acceleration (0 to 0.071 m/s2). The blue curve represents the bus's acceleration level, value from 0.290 to 1 m/s2, and the car's acceleration (0.071 to 0.29 m/s2) is between the train and the tram. Based on Figure 5, we choose the vehicle type by best fitting to each Gaussian distribution curve: train = [0, 0.071], car = [0.071, 0.29], and bus = [0.29, 1.0].

In Table 1, we evaluate our additional algorithm for detecting the vehicle type. We present the vehicle type classification accuracy for the 15 vehicle-riding segments contained in our 10 captured datasets. The left column shows the average acceleration value for each activity segment. The middle column shows the vehicle type classification. The right column indicates how many samples exist in each activity segment. While 13 segments were correctly classified, the types for 2 segments (no. 7 and 9) were incorrectly identified. For no. 7,

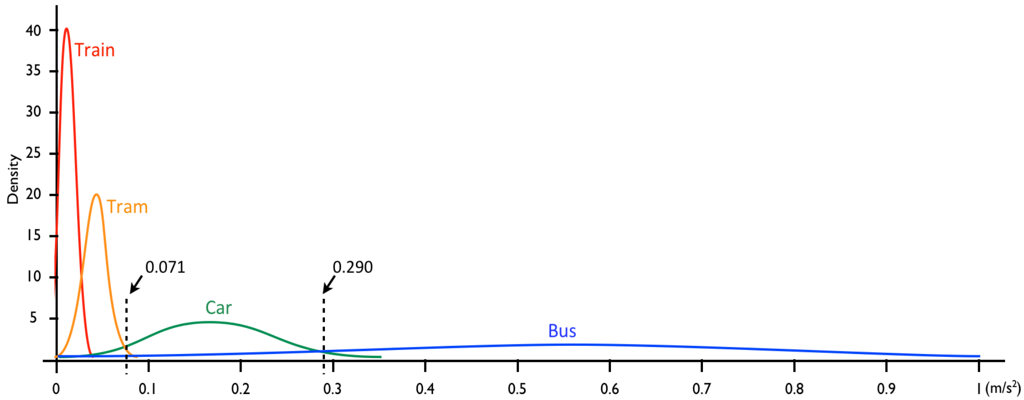



*Figure 5*
*Vehicle Type Accelerations. We show Gaussian distribution curves of the acceleration level among the vehicle types (Train/Tram, Car, Bus). Train/Tram has very low average acceleration value and Bus has relatively higher average acceleration value.*

*Table 1*
*Accuracy of vehicle type detection.*

| No. | Ground truth data / Average acceleration | Detection | Number of sensing counts |
|---|---|---|---|
| 1 | Tram / 0.018 | Tram | 256 |
| 2 | Bus / 0.418 | Bus | 520 |
| 3 | Bus / 0.371 | Bus | 95 |
| 4 | Tram / 0.027 | Tram | 185 |
| 5 | Bus / 0.380 | Bus | 220 |
| 6 | Train / 0.032 | Train | 280 |
| 7 | Bus / 0.103 | Car (wrong detection) | 450 |
| 8 | Car / 0.084 | Car | 320 |
| 9 | Car / 0.300 | Bus (wrong detection) | 395 |
| 10 | Tram / 0.042 | Tram | 416 |
| 11 | Tram / 0.044 | Tram | 70 |
| 12 | Bus / 0.325 | Bus | 230 |
| 13 | Bus / 0.293 | Bus | 255 |
| 14 | Tram / 0.025 | Tram | 790 |
| 15 | Bus / 0.418 | Bus | 500 |
| Accuracy: 82.691 (%) | | Error counts: 845 / Total counts: 4882 | |

the acceleration is lower than expected because the bus remained stationary at a stop for a considerable amount of time. The acceleration of no. 9 was slightly greater than expected due to unaccounted for aggressive car driving. Altogether, the vehicle type classification accuracy was quite good at 82.69%.

## CONCLUSIONS AND FUTURE CONTRIBUTION

We have introduced the novel idea of a crowdsourcing urban simulation platform, and a method to detect transportation mode and vehicle type using a smart phone sensor. Such development requires research to be conducted in numerous disciplines: social sensing, urban sustainability, mobile networking, activity detection, behaviour pattern analysis, and social network services. In this paper, we developed and presented the algorithm to detect user activity using by sensor. The algorithm exploits two observations: 1) walking activity has significantly different acceleration levels as compared to other transportation modes, and 2) every vehicle-riding activity is always surrounded by walking activity. By these findings, we implemented a walking detection algorithm, a vehicle activity packaging procedure, and a vehicle type classification method. Finally, we provide a Java-based Android smart phone application implementing the approach.

The collected data and the user feedback will help to deepen the understanding of how crowdsourcing techniques can be applied in this context. The results will provide directions for future work that builds on these techniques but will operate at larger scale. The collected data will be available for in-depth analysis independent of individual users, and will deliver inputs on how urban simulation can profit from real-user input. Thus, this research can be seen as a new paradigm of how urban simulation can include urban complexity arising inconstant and unpredictable human behaviour. More generally, the results will constitute a practical application of mobile crowdsourcing that goes beyond typical commercial applications by targeting the individual as well as decision-makers.

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