User Behaviour Captured by Mobile Phones

Wouter B. Teeuw, Johan Koolwaaij, and Arjan Peddemors

Novay, Capitool 15, 7521 PL Enschede, The Netherlands
{wouter.teeuw,johan.koolwaaij,arjan.peddemors}@novay.nl

Abstract. The i-Zone initiative proposes a new approach to urban mobility management by using the latest mobile ICT technologies. It is about mobile phones that measure and analyse user behaviour in order to influence travel behaviour. By providing feedback to the traveller (self monitoring), by information sharing, or by providing positive incentives to travellers by road authorities and other stakeholders, improved mobility in a city may be achieved. The information is targeted on individual travel behaviour, and thus allows a personalized approach to influence travel behaviour. This enables a shift from a focus on intelligent transport systems, with the emphasis on infrastructure and car-to-car systems, to a more human-centric approach based on ambient intelligence.

Keywords: mobile persuasion, mobility management, tracking and tracing, automatic behaviour analysis, influencing behaviour.

1 Introduction

The most common sensor used for observing the public domain is video surveillance, often applied for reasons of public safety. However, video is just one sensor like there are many sensors for many applications. The Sensor City initiative, e.g., implements a large-scale urban measuring network that will enable various applications for complex sensor systems to be developed for practical use like noise, pollution, or travel time prediction in public spaces [1]. Also, the combination of different sensors enhances results. With respect to face recognition, for example, Hulsebosch and Ebben show that the difficult problem of identification in (semi)public spaces can be reduced to a verification problem –with much more reliability– by taking other sensors, in particular mobile phones, into account [2]. An entirely new development is participatory or urban sensing, in the sense of people like you and me who are, equipped with today's mobile and web technology, observing the public space and share the results with everyone using social media.

This paper is about using mobile phones to measure, analyse, and eventually influence behaviour in public spaces. We use urban mobility as a (first) case. In our opinion, mobile phones are core components for future appliances anyhow, and for urban mobility management in particular. This paper is organised as follows. Section 2 explains the challenges in the domain of urban mobility and how mobile phones can be used to measure traffic flows. Section 3 describes the state of the art

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with respect to influencing travel behaviour, with again a focus on the role of mobile phones. Section 4 describes the i-Zone project in which we implemented a pilot platform to measure and analyse travel behaviour, in order to influence it positively. In section 5 we present some preliminary results of analysing travel behaviour. Section 6 ends with our conclusions and further research issues.

2 Using Mobile Phones to Measure Urban Mobility

Managing urban mobility means dealing with conflicting interests: Visitors and employees want to enhance mobility while at the same time municipalities or road authorities want to reduce traffic to enhance accessibility and reduce pollution. This is a common challenge to all major cities in Europe. How to deal with these conflicting system and personal objectives? The challenge is to achieve system goals like reduced congestion, reduced air pollution or improved safety by influencing personal goals in terms of stimulating people to change their individual travelling behaviour. Changing urban mobility patterns basically means changing the behaviour of people, i.e., replacing the one habit by another (preferably more optimal) habit or motivating people to change. Therefore, a human-centred approach is needed to encourage different travel behaviour. This is exactly where personal, mobile devices and Ambient Intelligence fit in perfectly.

We observe that much research and development in ‘intelligent transport systems (ITS)’ focuses on efforts to add information and communications technology to transport infrastructure and vehicles. What Ambient Intelligence adds to this developments is the focus on people and their personal mobile devices rather than vehicles and in-car systems. The technology becomes invisible, which shifts the focus on the traveller. We claim Ambient Intelligence technology may help to achieve system goals like reduced congestion, reduced air pollution or improved safety by influencing personal goals in terms of stimulating people to change their individual travelling behaviour.

For other reasons, transportation is mentioned among the promising application domains for Ambient Intelligence technology as well, together with domains as smart homes or smart offices (workplaces) and healthcare [3]. These domains coincide the application domains of the ‘Internet of Things’, which refers to the pervasive presence of a variety of objects (or ‘things’) that are able to interact with each other and to cooperate to reach common goals [4]. For example, the domain of transportation is characterized by the emergence of advanced cars, trains and buses that become more and more instrumented with sensors and actuators. The same holds for the roads and/or rails themselves that send information to traffic control sites, which in turn monitor and influence transportation vehicles. Apart from the logistics and monitoring issues, applications focus on assisted driving (like collision avoidance), mobile ticketing and augmented maps.

Besides, in-car navigation systems as well as mobile phones of users are used to track vehicles. Measuring and recognizing behavior using mobile devices is an emerging research field. In general, dedicated monitoring infrastructures systems are used to acquire traffic flow information. They mainly use inductive loop detectors or video cameras. Herrera et al. [5] propose to use in-vehicle GPS-enabled mobile phones to get the same information. Their experiments include 100 vehicles driving around with GPS-enabled mobile phones for 8 h on a freeways. Results show that 2-3% penetration of cell phones in the driver population provides accurate information on the velocity of the traffic flow. Personal travel statistics for households are currently mainly gathered by diary surveys (writing down all trips). Compared with those self-report surveys, mobile phones might be more accurate. Experiments of Stopher et al. [6] show, e.g., that the average number of trips per person per day is significantly higher from GPS respondents than from dairy respondents. Yang et al. [7] present how accelerometer and GPS features may be used to recognize physical activity, in particular to classify a stationary, walking, running, cycling or in-vehicle mode. Reddy et al. [8] show that in this way accuracy levels up to 94% are reached (Nokia n95 phone). It is not possible, however, to distinguish between different types of motorized transport (bus, car, train). Reddy et al. propose to use in-situ experience sampling for these purposes. Also, they note the need for energy efficient classification methods. Nonetheless, mobile phones seem very suited to gather information on personal travel statistics.

3 A Personal Approach to Influence Travel Behaviour

Current measures to influence and manage urban mobility may range from parking bans or speed ramps to discourage car usage, to blocking off access roads entirely, e.g. during rush hours. Some measures depend on ICT, with the electronic toll collection and zones with congestion pricing as well-known examples. A disadvantage of restrictive measures is that they are basically involuntarily and inflexible. Therefore, they are not a sustainable solution. As soon as someone is given the opportunity to get round the banning order, one will certainly do. These measures may even force people to make a detour, only moving problems. Therefore, one should make use of rewards rather than restrictions.

An example are ‘monetized’ inducements for adopting particular travel practices like discounted tickets for using public transport at certain times, public transport price reductions due to bulk or annual purchase, or discounted rates for entrance to certain tourist and visitor attractions for those who arrive by train or bus. The clearest evidence of the impact of financial reward on travel behaviour is that of the initiative *Spitsmijden* in the Netherlands [9] where financial inducements have shown to reduce car travel at peak times.

These forms of incentives are not particularly new and have been in widespread use throughout Europe for some time. The evidence suggests that they can influence particular journeys for particular purposes, but it is less clear that they can be used to influence people away from routine car travel, such as commuter traffic. Forms of incentives that reward longer term behaviour such as loyalty bonuses are widespread in the retail sector but less widely applied in transport. Ambient Intelligence (AmI) technology and mobile devices might be used to learn long-term behaviour and change habits in an ambient way. Current AmI technology enables a personal advice to be based on the actual data of the transport systems. The ITRAVEL project [10], for example, offers a service platform for the connected traveller to assist in context-aware, personalized travel planning prior to and during an actual journey. Or the social mobile application Waze [11] provides free GPS navigation based on the live conditions on the road, measured by other Waze users.

Ambient Intelligence enables a personal travel advice, anticipating on what the system has learnt from the historical traffic situation and the personal travel behaviour and preferences. In recent years, there has been much interest using direct personalized techniques to provide individuals or households with information enabling them to reduce car use and/or increasing the use of more sustainable transport modes. Salim [12] introduces the concept of adaptive mobile mashup, which is a learning system that uses context-aware filtering to selectively present or visualize integrated information in order to reach a targeted behaviour. Froehlich et al. [13] researched the use of displays on mobile phones to give users feedback about sensed and self-reported transportation behaviour. Both examples use mobile devices that, according to Fogg [14], are the most important platform for changing human behavior. To change the behaviour of people, personal mobile devices are key.

4 Incentive Zone Case

We apply the above mentioned principles of personalized advice, incentives and communities to a specific geographical area in Enschede, The Netherlands, which we called an Incentive Zone (in short: i-Zone). The objective of i-Zone is 5% less traffic (measured in car kilometres in a specific area) during the rush hours. We want to achieve this system goal by influencing personal goals in terms of stimulating people to change their individual travelling behaviour.

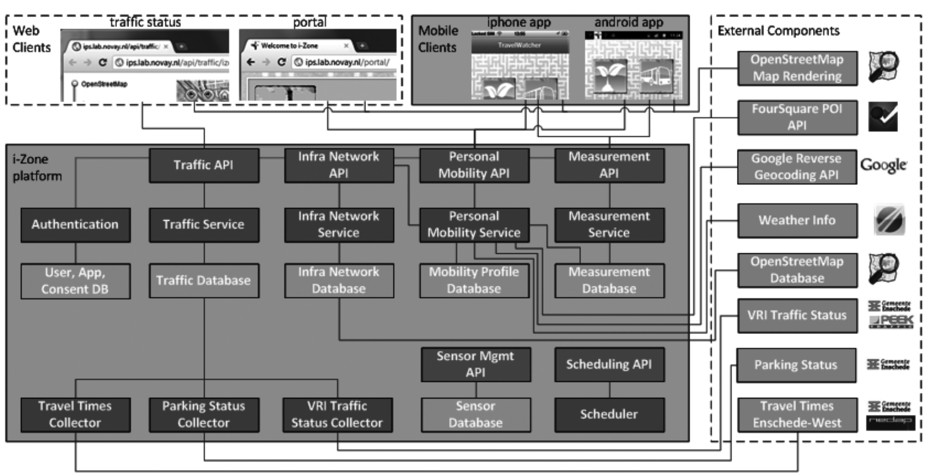

Fig. 1. Architecture of the i-Zone platform

Fig. 1 shows the architecture of the i-Zone platform. The idea of a platform approach means that there is a platform that gathers data about the status of the traffic network in the city as well as data on a personal level, aggregates and analyses this data and provides meaning full information toward applications that run on top of the platform. Currently, there is only one application called TravelWatcher (implemented as iPhone and Android app). We currently collect infrastructure data from in-pavement detectors about the number of cars that pass the (main) traffic lights (VRI Traffic), the available number of free parking lots in the urban parking garages, and travel times collected by an Automatic Number Plate Recognition system (ANPR). Besides, we use data from external sources, in particular map related data from Google and Open Street Map, places from Foursquare, and weather info from Buienradar.nl.

Most relevant for behaviour analysis, however, we collect data on the personal level. To collect individual information, as well as to distribute incentives that are triggered by the context and the individual behaviour of citizens, i-Zone uses IYOUIT concepts [15]. IYOUIT is mobile service to share personal experiences or context data with others while on the go [16]. An application (measure tool) has been implemented that reads the location (GPS), acceleration, and electronic compass sensors on the mobile phones of i-Zone participants, and automatically detects the trips people make. More detailed analysis of mobility data is performed on the i-Zone platform server. The measurement tool has currently been implemented for iPhone and Android smart phones.

In the i-Zone web portal, users can register themselves, and are presented with a wealth of personal mobility statistics, as described in the next section. Also, using a simple and transparent interface, users can decide which personal information they want to make available for which application. On a website, the current or expected traffic status is shown as well.

Fig. 2. Screenshots of the TravelWatcher mobile sensing application

Fig. 2 shows four screenshots of the mobile measurement application that has been developed. The application has been named TravelWatcher and records trips on a 24/7 basis, automatically recognizes modality choices, visited places, frequent routes and mobility footprint. It will show neat statistics on the personal balance between human powered transport (walking, cycling), fuel powered personal transport (car, motor) and public transport (bus, train, plane). Finally, situational dependencies are charted for their personal modality choices, and show the impact of rush hour, rain or fog, and events on the choices they make.

TravelWatcher provides a means for self-monitoring, one of the seven strategies that are commonly used in persuasive technology [17], which is already an incentive to change behaviour. Self-monitoring allows people to monitor their own mobility patterns and to inform them how they could modify their travel behaviour. A next step is to provide commercial incentives, like an employer offering an e-bike or a restaurant with a food offering to stimulate new ways of working an travelling; and to evaluate the effect on travel behaviour. For this reason, the European SUNSET project [18] has been developed, which will use i-Zone as a living lab. The community aspect is taken care of by creating groups of users (e.g. users belonging to an employer) and by introducing a gaming element (earning points by travel behaviour). These issues are currently under development.

5 Analysing Travel Behaviour

The data collected by mobile phones is combined with external (sensor) sources and analysed to provide enriched user data. We are currently able to automatically analyse the following travel behaviour:

- The detection of single-modality trips, and an end-to-end journey by concatenating consecutive single-modality trips. Trips are detected on the client (mobile phone) using location sensors (GPS, GSM, WiFi). Being present for at least five minutes at a certain location marks the end of a trip. Errors may occur due to, e.g., long waiting for a traffic light or in a traffic queue, inaccurate location information from the sensors, or switch back and forth between GSM masts. This is periodically corrected at the server side, e.g., concatenating trips into end-to-end journeys or removing ‘ghost trips’.
- Automatic detection of personal places, those places frequently visited by the user (on an address level and name level, e.g., the name of a shop). Places are the start and end points of trips and automatically named by either the address (from map information) or a name (Foursquare places). It is possible to manually overwrite the names.
- Automatic classification of personal places: what is the user’s home, office, school, etc. The time of day is used for these purposes: where you regularly sleeps is your home, where you are at office times is your work or school, depending on the kind of place, etc.
- Automatic detection of the modality used: is the user travelling by car, bike, train, etc. The algorithms mainly use speed and map information to automatically detect this information. As opposed to approaches using accelerometers, we can distinguish between types of motorized transport (car, bus, train) by using location dependent models (map information).

- Automatic analysis of regular trips: Identifying the frequent trips the user makes. Trips are identified by the start and end place and the mode of transport used.
- Accompany detection: automatic analysing whether people travel or stay together, as an indication of people carpooling, travelling together on a business trip, or people who could potentially do car sharing on specific days.

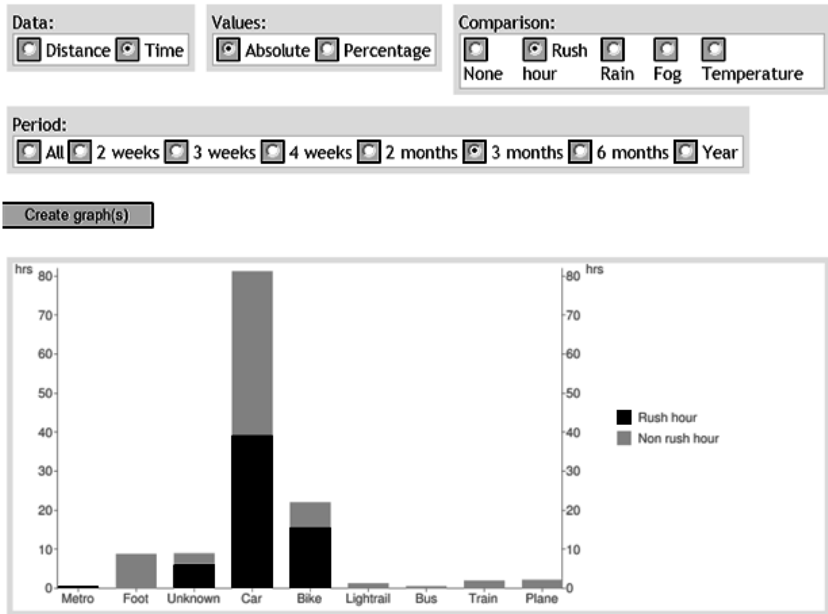

Fig. 3. Example of a personal mobility pattern

The pilot system is currently in a test phase with, at the moment, 40 users, who made more than 5000 trips with over 800 cities involved. The about 30.000 hours of location data gathered allows behaviour analysis on both an individual and an anonymous group level. For example, on a personal level one may analyse the modalities used in relationship to, e.g., the weather or rush hours (see Fig. 3). Identically, group modality statistic are possible. Other group analyses include, e.g., an analysis of all participants going to a specific place during a specific period.

Our system is a reference-implementation that is currently in a test phase, searching for its potential. The quality of the system is continuously improving. Users are able to manually correct erroneously recognized modalities or improve place classifications. Automatic modality detection is done in a batch process at night. Based on trips that are manually tagged before they are automatically labelled, we have an indication of the quality of our system. From the over 1000 manually tagged trips, 75.1% appears to be correctly classified. For the users in our pilot area Enschede 76.7% is correct (see Fig. 4). Currently, all trips are automatically classified. They can be manually corrected by users in case the modality is not correct. An experiment to compare automatic classification with a dairy survey is still to be planned.

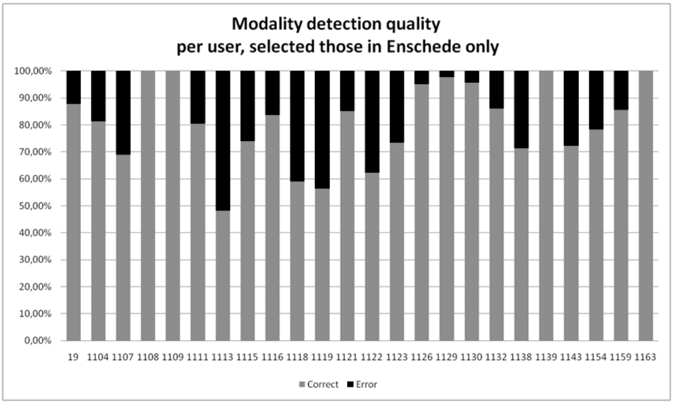

Fig. 4. Quality of modality detection for the Enschede users

6 Outlook and Conclusions

To our opinion, the research agenda for mobility should shift from intelligent transport systems, with a lot of emphasis on infrastructure and car-to-car systems, to a more human-centric approach. This fits the research agenda of ambient intelligence, in particular the ambient technology focusing on learning systems for personalization, adaptation and anticipation on behaviour. Mobile phones are important sensors and actuators for these purposes. Using mobile phones one may measure behaviour on both an individual, and a group level; as well as one may influence behaviour. For, persuasive technologies are close to mobile systems [14].

From our current experiences, we observe four main areas for further research. First, advances in the analysis of human behaviour by, e.g., the integration of many real-time sensors from personal devices and (road) infrastructures, detect modality transitions even better, and to estimate mobility consequences in terms of time, costs and emissions. Second, research on the role of mobiles in ambient environments. In our current system, the users are in control. Ambient Intelligence means the environments is aware of the presence of people and reacts on it. The environment may trace mobiles as well, e.g., based on Bluetooth, for which the technology exists (and is applied in traffic as well [19]). This allows additional behaviour analysis for users that do not want to install monitoring software. Third, power management for mobile devices needs research. For, using GPS to trace mobiles uses too much battery power. As long this issue is not solved by better batteries or energy harvesting itself, smart algorithms must 'solve' the problem by only track and trace if necessary, and using personal historic information to decide if detailed location measurements are really necessary for a regular commuter trip. And fourth, privacy is a research issue. We need to find the balance between empowering a user with all kind of information on the one hand, and the protection of personal data and the (implicit) influencing of behaviour on the other hand [20].

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