Transportation Behavior Sensing using Smartphones

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Abstract
Inferring context information from periods of transportation is an important subtopic of the wider field of mobile and ubiquitous sensing. The transportation behavior reveals information about individual's physical activity, preferred transit types, mobility patterns and important places. As a platform for mobile sensing, we employ common smartphones, which have matured into a quintessential instrument with both new challenges and new possibilities. The presented research contributes by addressing several key constraints of smartphone based context sensing, including determining the phone's orientation in real-time, introducing energy-efficient sensor management, and advanced feature engineering from accelerometer.

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Transportation Behavior, Mobile Sensing

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C.2.4 [Computer-Communication Networks]: [Distributed System]; H.4.m [Information Systems]: Applications—*Miscellaneous*

General Terms
Algorithms, Experimentation

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Introduction and Related work

The presence of smartphones is rapidly becoming ubiquitous in urban environments with over a billion smartphones in use worldwide[1]. Simultaneously, the available sensing capabilities, along with high computational and communication efficiency have enabled smartphones to mature into an attractive platform for context inference about the user and the environment. In this research, we focus on the *Transportation behavior*, which covers user activities during periods of transportation. Transportation behavior of human activity is the central contributor for the user's daily physical activity and personal CO2 footprint [4, 14]. Over time, transportation behavior can reveal information about the user's meaningful places, routines and behavior [1]. When applied in large-scale, the transportation behavior sensing can be used for human mobility tracking and modeling, which could provide valuable information for urban planning and designing transportation networks [17].

The existing research has considered various aspects of smartphone based transportation behavior. Popular topics on traffic and transportation monitoring include, e.g., transportation mode detection [1, 15], tracking and predicting arrival time of transit vehicles [8, 18], and estimating road and traffic conditions [9, 13]. On personal scale, the existing research has focused on estimating driver's driving behavior and condition [3, 2], detecting dangerous situations such as lane departures [16] and personal estimation of CO2 emissions [4, 14].

From the available sensors on mobile phones, accelerometers have been ubiquitously used to track vehicle movement. The accelerometer is an attractive choice due to its energy-efficiency and capability to capture rich information from the user's activities. Moreover, accelerometers can use the earth's gravity as a robust reference for downwards direction and as such are more informed than other inertial sensors. Additional sensors, such as magnetometer and gyroscope have been used to track direction of user's movement and to detect driving maneuvers [2, 3]. GPS and WiFi sensors have been widely used to determining user's location and for trajectory tracking [8], which in turn have been used to estimate traffic conditions and delays [18].

In real-world deployment, it is vital to remember that the device has other primary functions, and the transportation behavior sensing should occur continuously and unobtrusively in the background with reasonable energy consumption. Consequently, no assumptions about the use of phone, e.g., phone's orientation, placement or user interaction, should be made. Similarly, the system's energy-efficiency should be a critical concern when choosing sensors and designing sampling strategies from the wide range of sensors available from modern smartphones.

The present research contributes novel projections of accelerometer measurements and demonstrates their effectiveness in capturing high level contextual information, such as the fuel consumption, sustainability of personal transportation behavior and skill assessment of the vehicle's driver. Relying solely on the accelerometer improves the robustness of the sensing in situations where other sensors might not be usable (e.g., GPS underground or GSM outside cell tower coverage) as well as provides an energy-efficient

[1] http://www.strategyanalytics.com/, retrieved [10.01.2013]

alternative to prior works that have relied on combinations of multiple sensors.

Research Goals and Methodology

In consideration of the above outlined challenges, the present research aims to contribute with the following algorithmic (A), enabling (E) and system (S) level contributions.

- A1: Algorithm for robust and real-time smartphone orientation estimation.
- A2: Hierarchical, adaptive sensor selection and management scheme, based on an utility sensitive AdaBoost algorithm.
- E1: Advanced feature engineering from accelerometer to capture information about transportation behavior.
- E2: Transportation mode detection system, relying on advanced feature engineering from accelerometer.
- S1: Application to asses driver's driving behavior and fuel consumption, and to provide feedback how to improve driving style.

The current state of research has completed points E1 and E2, while majority of the work for A1 and A2 has been carried out.

Phone orientation In order to extract information from the phone's inertial sensors, the system has to overcome the problem of varying phone orientation. The problem has been approached [15, 19, 20] by using orientation invariant features, e.g., by first computing the L_2-norm (magnitude), defined as:

$$a = (a_x^2 + a_y^2 + a_z^2)^{1/2}.$$

Using the L2-norm, however, emphasizes vertical acceleration, as acceleration caused by gravity can easily mask even substantial horizontal acceleration. Alternatively, the phone's orientation can be estimated by using a gravity component estimation obtained from the accelerometer [12, 11, 10]. Currently, the most cited method [12] for estimating gravity component is to use the mean of the accelerometer measurements over a sufficient long window. This approach, however, is only effective under an assumption that noise and observed acceleration are uncorrelated over time, which does not hold during sustained acceleration, e.g., acceleration periods of motorised transportation.

As the first contribution of our research, we have developed a novel accelerometer based *Robust Gravity Component Estimation Technique* [6]. Our technique improves on the previous methods for this task, which are not robust under changing orientation of the accelerometer or when sustained, directional acceleration is present. Our solution estimates the gravity component opportunistically by identifying periods where the sensor is stationary or the movement is approximately constant, and estimating the gravity as the average of these periods considering the reliability and recentness of the measurements. Our gravity estimation algorithm enables accurate reconstruction of horizontal and vertical acceleration components, regardless of the orientation of the sensor, or changes in it.

Analysis of Accelerometer Projections To demonstrate the efficiency of the accelerometer projections, we have developed an *Accelerometer based Transportation Mode Detection* system [6]. Utilizing the gravity eliminated horizontal acceleration projection, we construct a novel set of peak features capable of capturing the vehicle's acceleration and deceleration patterns. A thorough evaluation covering 150 hours of data from 4 countries and 16 users demonstrates, that our solution is able to provide state-of-art detection accuracy, while only using the smartphone's embedded accelerometer.

In terms on ongoing and future research, we are currently looking into further analysis of the acceleration and breaking patterns extracted from the accelerometer to assess the driver's driving abilities. The accelerometer features will be augmented with information from other gyroscope and magnetometer if needed to gather more information from turning maneuvers. Additional expected contributions from this direction are an accurate, real-time estimation of fuel consumption and CO_2 emissions, which could be used to offer feedback on how to improve driving habits.

Further research concepts following this theme of study include detecting potentially dangerous situations in transportation, e.g., risky driving maneuvers or falling asleep behind the wheel. A similar analysis of acceleration and breaking patterns, along with timing the intermittent stationary periods, could be used for public transportation to enable accelerometer based participatory sensing for vehicle tracking when GPS is not available or reasonable, e.g., while traveling underground or for energy-efficiency reasons. Finally, when applied in a larger scale, the acceleration and breaking patters could be used to estimate the prevalent traffic conditions and identify congested sections.

Sensor Selection While many interesting aspects of transportation behavior sensing can be realized with only accelerometer, some require additional sensor information about, e.g., user's location or direction of movement. To support the use of additional sensors, we have developed an initial version of *HASMET*, a Hierarchical adaptive sensor-management scheme for energy-efficient transportation behavior monitoring [5]. HASMET is a classification framework which decomposes a transportation monitoring task into smaller subtasks. The key benefits from this design are (i) specialized classifiers for each subtask, (ii) ability to employ only the relevant sensors, and (iii) flexibility to provide different granularities of information based on application demands.

At the core of HASMET is an *Energy-Aware Adaptive Boosting* algorithm, an extension for AdaBoost which can be set to (i) find a set of sensors/features which provide optimal detection accuracy given a maximum total energy, or (ii) balance between energy and accuracy given an utility function between the two. An initial version of this algorithm has been implemented, which modifies the loss of the algorithm to also consider energy cost associated with the features.

Application Areas To confirm the real-world applicability of our contributions, we combine controlled data collections and longitudinal deployments of novel mobile applications. As an example of latter, the transportation mode detection module has been integrated as part of MatkaHupi, a persuasive mobile application for sustainable mobility [7]. As another ongoing work, we utilize our accelerometer analysis in a Smart Traffic application to assess the user's driving skills and provide feedback how to improve them.

Objectives for the Doctoral School

I have two main expectations for the doctoral school. First, I would like to receive feedback and comments from people with more experience and a broad view of the research area. Second, I wish to exchange ideas and get to know other doctoral students. While some of the contributions I plan to include in my dissertation are nearly completed, I would still like to clarify other topics which have only recently begun, as well as to receive ideas on new interesting research ideas.

Biography

The PhD program has been started from the beginning of 2013 and is planned to finish by the end of year 2015. The doctoral studies will be primarily conducted within the Algorithm and Machine Learning group at the Helsinki Institute for Information Technology, HIIT, Computer Science Department, University of Helsinki. Specifically, the thesis is conducted in affiliation with the Internet of Things program. The progress and direction of the doctoral studies will be supervised by Adj. Prof. Nurmi, P. and Prof. Tarkoma, S. Additional mentoring will be provided by Adj. Prof. Floreen, P. and Prof. Asokan, N.

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