Computers, Environment and Urban Systems 58 (2016) 52–59

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

Making pervasive sensing possible: Effective travel mode sensing based on smartphones

Xiaolu Zhou [a,*], Wei Yu [b], William C. Sullivan [c]

[a] Department of Geology and Geography, Georgia Southern University, 68 Georgia Ave, Herty Bldg 0201, Statesboro, GA 30460, United States
[b] Department of Mechanical Engineering, Georgia Southern University, P.O.Box 8046, Statesboro, GA, 30460-8046, United States
[c] Department of Landscape Architecture, University of Illinois at Urbana–Champaign, 101 Buell Hall, 611 E. Taft, Champaign, IL 61820, United States

ARTICLE INFO

Article history:
Received 30 August 2015
Received in revised form 19 February 2016
Accepted 6 March 2016
Available online xxxx

Keywords:
Smartphone sensing
Mode detection
Active travel
Geographic information systems

ABSTRACT

Smartphones with embedded Global Positioning Systems (GPS) sensors and accelerometers provide outstanding opportunities to gather information about transportation modes. In comparison to traditional approaches of measuring travel behavior, such as self-reports and travel behavior surveys, a smartphone application that tracks movement increases spatiotemporal resolution and reduces the burden on individuals to manually recall and log travel behavior. Studies using smartphones to detect travel modes mainly use segmentation approaches, which divide movement data into single-mode segments. These approaches hinge on the accurate detection of transitional nodes, which are occasionally difficult to identify. In this study, we proposed a method to detect travel modes based on the chained random forest (RF) model, which automatically classifies smartphone data into different travel modes without using a prior search for transitional nodes. We evaluated the proposed method by collecting and analyzing 12 people's travel behavior spanning six days. The proposed method achieved 93.8% overall accuracy and performed well in both indoor and outdoor environments. This travel mode detection model offers potentials in conducting pervasive sensing, which will eventually benefit many areas of research that require large scale travel behavior monitoring.

1. Introduction

Understanding human transportation modes (e.g., walking, running, driving etc.) is critical in many areas of research (Biljecki, Ledoux, & van Oosterom, 2013). In transport planning and traffic management, understanding where and when people travel and their mode of travel is necessary in assessing travel cost, predicting public transport demand, identifying spots where traffic congestion occurs, and optimizing urban transport systems (Bohte & Maat, 2009). In urban design and public health, researchers work to understand how and where people travel in order to measure the association between environmental features and people's choice of travel modes (Sallis et al., 2006). In environmental epidemiology, being able to measure transportation modes is essential for studies concerning air pollution exposure because air pollutants vary significantly by location and travel modes (Wu et al., 2011). Thus, detecting travel routes, travel time, and travel modes is crucial in many areas of research.

Several methods have been used to measure travel behavior in previous studies. Publicly available datasets on travel behavior are usually aggregated datasets, static in both space and time (Jerrett et al., 2003). Self-reported travel logs are sometimes biased and hardly reflect specific travel times or the exact paths taken. Pedometers and accelerometers cannot provide the location where exercise or travel takes place (Maddison & Mhurchu, 2009). Moreover, wearing devices such as GPS sensors or accelerometers can be cumbersome and technically challenging for some research participants. These limitations call for new approaches to collect rich information about travel behaviors that can be used to understand not only the route taken, but also the method of travel.

In this context, smartphones offer a platform to overcome the challenges that previous measures face. Smartphones, which have been called “urban sensing” devices (Cuff, Hansen, & Kang, 2008), are less cumbersome than GPS systems, and applications on smartphones can be customized to collect data regarding location, time, and types of movement. More importantly, compared to other devices, smartphones are able to collect and transfer travel data in real time, and offer opportunities to model human mobility in a timely fashion. Hence, an increasing number of studies have used smartphones to examine travel patterns in urban areas (Nitsche, Widhalm, Breuss, Brändle, & Maurer, 2014; Shin et al., 2015).

Despite the usefulness of smartphones, there are challenges to overcome. Several studies have reported difficulties associated with detecting travel modes based on the GPS and accelerometer data from smartphones. Most prior studies used segmentation approaches,

* Corresponding author.
E-mail addresses: xzhou@georgiasouthern.edu (X. Zhou), wyu@georgiasouthern.edu (W. Yu), wcsulliv@illinois.edu (W.C. Sullivan).

http://dx.doi.org/10.1016/j.compenvurbsys.2016.03.001
0198-9715/

which divide movement data into single-mode segments. Different approaches have been used to detect the single-mode segments, such as a low speed threshold (Biljecki et al., 2013) or walking segments as separators (Shin et al., 2015). These approaches rely on the accurate detection of transitional nodes. There are, however, many circumstances in which transitional nodes are difficult to detect. For instance, when a person starts driving a car right after getting off a bicycle, in this case, using the walking segment between the bike and the car to separate the two modes becomes difficult to calculate. Cases like these reduce the classification accuracy of segmentation-based methods.

Segmentation-based methods also have difficulties with a single contiguous transportation. A long bike trip, for instance, is likely to include a number of short stops. Methods based on segmentations may generate unnecessary short segments.

Given these challenges, we sought to develop and evaluate a chained random forest (RF) model that automatically classifies smartphone data into different travel modes without prior segmentation. In the following section, we summarize recent work in this area and elaborate on the main challenges. Details about the proposed approach are introduced in Section 3. Section 4 describes the model evaluation based on a field experiment. Section 5 and Section 6 discuss the contributions of this work and conclude this study.

2. Related work

2.1. Advancement of travel behavior measures

The increasing prevalence of smartphones has created an opportunity to use them to detect and measure travel behavior (Franko & Tirrell, 2012). Smartphones with embedded sensors arm researchers with opportunities to deploy mobile sensing applications with an unprecedented efficiency and a much broader geographical context (Miluzzo, 2011). In a pilot study, Kerr et al. (2011) found that, in comparison with independent GPS devices, assisted GPS devices in smartphones provided faster fixes and fewer participant dropouts. In addition, smartphones alleviated the burden on participants of using unfamiliar research instruments (Kerr et al., 2011). Moreover, cellular networks allowed real time data transfer and modeling. All these merits of using smartphone to measure travel behavior depend on accurate travel mode detection.

2.2. Travel mode detection

Scholars have used smartphones to collect travel data. Many smartphone applications, however, have required users to manually report their transportation modes (e.g., walking, biking, bus). The additional tasks of reporting transportation modes restricted the popularity of these applications, and very likely, the accuracy of the data collected (Santos, Cardoso, Ferreira, Diniz, & Chaínho, 2010; Shin et al., 2015).

Some studies automatically detected travel modes based on smartphone platforms (Hemminki, Nurmi, & Tarkoma, 2013; Manzoni, Maniloff, Kloeckl, & Ratti, 2010). These efforts typically classify travel modes using two types of information: locational data captured by the locationing approaches (such as GPS, Wi-Fi positioning, cell tower triangulation) or vibration data obtained by accelerometer (Reddy, Burke, Estrin, Hansen, & Srivastava, 2008). Predictors derived from locational sensors included speed, acceleration, direction, and spatial accuracy. In general, the speed between two consecutive points has been the main predictor in most classification methods (Biljecki et al., 2013; Bohte & Maat, 2009). Other studies used accelerometers to classify physical activity types. For instance, one study used a single tri-axial accelerometer placed on the waist to record the acceleration data. Using this method, five types of activities were classified with about 80% accuracy (Long, Yin, & Aarts, 2009).

Studies using smartphones to detect travel modes mostly use segmentation approaches that divide movement data into single-mode segments before computing travel mode classification (Nitsche et al., 2014). In order to calculate segments of tours, the first step is to identify points at which an obvious travel mode change occurs (transitional points). The criteria for the travel mode change vary according to the purposes of different studies (Wan & Lin, 2013). There are different approaches to achieve this goal. Waga et al. (2012) divided routes into segments based on similar speed. Wan and Lin (2013) used both speed and location criterion to detect change points, based on which movement data were divided into segments. Gong, Chen, Bialostozky, and Lawson (2012) used a rule-based approach to detect walk segments, and used the first and last points of the GPS data gap or the walk segments that were longer than 60 s as the travel mode change point. Shin et al. (2015) used walk segment detected by accelerometer features as the separator to detect other single-mode segments. In order to classify different modes of travel, previous studies have used different algorithms to identify various modes. Wu et al. (2011) used both user-defined rule-based models and learning-based models to classify based on GPS recordings. Xu, Ji, Chen, and Zhang (2010) used a speed-related fuzzy membership algorithm to divide GPS trajectories into mode segments. Shafique and Hato (2015) used support vector machines (SVM), adaptive boosting (AdaBoost), and decision trees to classify accelerometer data in three cities in Japan.

Approaches based on the single-mode segmentation often leave off some segments when transitional nodes are difficult to detect. In addition, a contiguous trip with single mode may be divided into many small segments if such trip comprises heterogeneous accelerations or intermittent stops. In this paper, we introduce a chained RF model including three layers of classifiers to detect different travel modes. The following section describes the design and implementation details of the classification model.

3. Methods

3.1. Accelerometer and GPS data

The accelerometer and GPS data we collected included three components: a timestamp, acceleration values along three axes, and geographic coordinates when the GPS signal is available. The timestamp identified the date and time the data were recorded. The acceleration values were derived from the accelerometer in smartphones that measure the acceleration of the device along three axes. The x-axis pointed in the cross direction (from left to right) of the device, the y-axis pointed in the longitudinal direction (from down to up) and the z-axis is orthogonal to the display of the device (Huang et al., 2010). The latitude and longitude values were captured by the embedded GPS unit.

3.2. Input features

3.2.1. Decompose acceleration

The accelerometer sensor in Android phones reports accelerations that involve a constant gravity force. In order to extract accelerations because of user's motion rather than gravity, we need to exclude the gravity component first. We used the mean values over a floating window of 30 adjacent points along three-axis to derive the vertical gravity vector $\boldsymbol{v_t} = (g_{xt}, g_{yt}, g_{zt})$ (Mizell, 2005). Once we get the gravity vector, for every accelerometer reading along three-axis $\boldsymbol{a_t} = (a_{xt}, a_{yt}, a_{zt})$, we can extract motion component of $\boldsymbol{d_t}$, by calculating $\boldsymbol{d_t} = \boldsymbol{a_t} - \boldsymbol{v_t}$. We also decompose $\boldsymbol{d_t}$ to vertical and horizontal directions by projecting $\boldsymbol{d_t}$ to the corresponding directions (Mizell, 2005). This procedure helps to split user motions into two important directions.