Travel Mode Identification with Smartphones

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Abstract

Personal trips in modern urban society usually involve multiple travel modes. To recognize a user's transportation mode is not only critical to the applications in personal context-awareness, but also contributes to the urban traffic operations, transportation planning and city design. While most of current practice often leverages infrastructure based fixed sensors or GPS for traffic mode recognition, the emergence of smartphone provides an alternative appealing way with its ever-growing computing, networking and sensing powers.

In this paper we propose a GPS and network- free method to detect user's travel mode using mobile phone sensors. Our application is built on the latest Android smartphone with multimodality sensors. By applying a hierarchical classification method, we achieve 100% accuracy in a binary classification wheelers/non-wheelers travel mode, and an average of 96.4% accuracy in a 10-fold cross validation with all six travel modes (buses, subways, cars, bicycling, walking, and jogging).

Keywords: Traffic Mode Identification, Vehicle Classification, Machine Learning, Smartphone Sensors

1. Introduction

Personal trips in modern urban society usually involve multiple travel modes, including passenger cars, buses, subway, pedestrian, bicycles, etc. Different travel modes have their own specific characteristics including travel speed, volume, fuel consumption, emission use, priority level, and vulnerability. Not only is recognizing transportation mode critical to understand people's travel behavior [1], but also such information help improving transportation planning, management and operations. For example, personal mobility accounts for about two-thirds of the total transportation energy use [2]. Understanding and assessing an individual's personal contribution to the emissions of a city requires personal travel diaries, including accurate information of travel mode. By leveraging information of travel mode, traffic signal control systems are able to treat each mode in an integrated way and achieve multi-modal traffic optimal control [3, 4]. Also travel mode information constitutes of the essential part of household travel diary data, which are essential for regional transportation planning.

Travel mode identification is a natural extension of vehicle classification, which only targets on motorized transportation. There are many existing technologies for vehicle classification. Most of current practice leverage infrastructure based fixed sensors, including pneumatic tubes, inductive loop detectors, piezoelectric sensors, Weigh-in-motion (WIM) systems, radar sensors, infrared sensors, acoustic sensors, and computer vision-based sensors [5]. However, traditional fixed sensors may suffer from following disadvantages: i) high installation and maintenance costs, ii) limitations under specific situations (e.g. inclement weather and saturated traffic) and iii) failure to obtain travel mode information in a complete trip rather than a few locations. n the past decade, given reduced cost in Global Positioning System (GPS), more and more studies focus on collecting personal travel data using GPS loggers [6]. GPS based floating sensors appear more appealing by providing individual trip-chain data with extremely low costs.

Another emerging type of floating sensors to obtain travel mode information is smartphone. As a necessary part of our wearable devices, smartphone becomes more and more sophisticated, with ever-growing computing, networking and sensing powers. Nowadays, smartphones can provide much more than GPS location information. They are usually equipped with accelerometer, gravity sensor, barometer, light sensor, gyroscope, compass and others. The advanced sensors equipped on the smartphone chips enable a rich variety of smartphone data mining applications such as users' activity recognition, including travel activities, from a simple locomotion (e.g. walking, jogging, walking downstairs, taking elevator, and etc.) to complex activities (driving, waving hands, dining, shopping, watching movies and etc.) (see [7] for a complete survey). Therefore, the smartphone can be considered as one of the best sources for crowd sourcing real time dynamics while travelling.

In this paper, we are particularly interested in using smartphones to automatically classify six different travel modes, including cars, walk, jogging, bicycles, buses and subway. To distinguish previous studies with online data such as GPS and GSM, in this study, we use offline data collected from other aforementioned sensors. Smartphones can be considered as a special form of wearable devices, which allow people to carry and move with the traffic flow and continuously collect personal travel activity information. Although the collection and sharing of massive mobile data need to overcome institutional (e.g., who should collect the data), policy (e.g., privacy issues), and technical challenges (e.g., bias of the collected samples), they do provide information (e.g., vehicle traces) that promises great advances in many science and engineering fields [5]. As mentioned above, smartphone can provide a variety of sensor data which can be easily processed to further obtain speeds, accelerations, decelerations, rotation, gravity, air pressure, temperature and humidity of the ambient environment, and orientation of the device. Since different travel modes tend to have different characteristics of speed variations, acceleration rates, rotation, and even temperature and humidity [8]. Therefore, this motivates us to use smartphone data for automatic travel model identification.

There still exist several challenges for using smartphones to classify travel mode. First, traditional classification method rely on online data such as GPS/GSM [5, 9, 10, 11, 12], of which the signal strength is unstable. In the urban area due to the interference of tall buildings and other signal towers, the accuracy of GPS data is lower. Not to mention that in a big city like New York there is no GPS/GIS signal inside subways. Second, the long term sensing and data storage on smartphone with full work load of sensors is both energy and resource consuming. The battery capacity and the computing resources are the main bottlenecks for context-aware applications [13, 14]. Third, although mobility is one of smartphones' biggest advantages for sensing, the fact that they are moving together with the human body can also introduce much noise for those sensors that are related to activities [15]. For example, the way a user holds a phone would affect the motion sensors' readings since they are related to how the phone is swinging with the user's body during moving.

In this paper, we present a method that aims to solve these problems. First, our method to detect travel modes using offline data (GPS/GSM free) get from up-to-date sensors like barometers and light sensors that are equipped on the latest smartphones. Thus we do not rely on the GPS and other data from networks. Second, our solution uses a hierarchical classification method that is designed with energy efficiency. It uses a single sensor to detect whether it is wheelers travelling like taking buses/subways/cars and bicycling, or other non-wheelers mode like walking or jogging. Then inside each subcategory, it will decide which sensors to use for further calculations. By doing so, it saves both computing resources and the energy that is costly by sensing, computing and data storage. Third, we do not only select the sensors that would involve less noise, but also we apply techniques like coordination rotation to get the phone gesture-independent data.

The rest of this paper organizes as follows. Section 2 conducts a brief literature review in travel mode identification. Section 3 presents the detailed method as well as the experiment for the traffic mode detection. Section 4 concludes the paper.

2. Literature Review

There is vast literature in travel mode identification (including vehicle classifications). Recently, more and more studies focus on travel mode identification with floating sensors, due to their various advantages over fixed sensors. Therefore, in this paper, we only consider floating sensor based approaches (see [5] for a detailed review for fixed sensor based methods). According to the types of sensors adopted, we further categorize the previous work into GPS-based and smartphone-based classification methods.

Majority of the early literature in travel survey, which leverages only GPS information (location, speeds, and derived acceleration data), are considered as GPS-based classification methods [16, 17, 18, 19, 20]. Support Vector Machine (SVM) is one of the most popular methods for classification. Zhang et al. (2011) performed a two-stage classification with SVMs. First stage identified three main travel-mode classes: pedestrian, bicycle, and motorized vehicles. Second stage further classified different classes of vehicles into cars, buses, trains and trams [21]. Bolbol et al. (2012) developed a moving window SVM to classify six travel modes from sparse GPS data [10]. Another study used SVMs with quadratic kernel functions for binary classification, which only considered passenger cars and trucks [5]. Several studies leveraged Geographic Information Systems (GIS) for better detection accuracy. GIS algorithms and GPS data were combined to detect five travel modes (walk, car, bus, subway, and commuter rail) in New York City [6]. Moreover, another study proposed a combined fuzzy logic and GIS-based algorithm to process raw GPS data. The algorithm was applied to GPS data collected in the highly complex Greater Copenhagen Area network in Denmark and detected trip legs and distinguished between five modes of transport [9]. A similar study with fuzzy pattern recognition was conducted in Shanghai, China [22]. Many algorithms presented in this category usually involve heavy data processing and transmission load on mobile devices that may exceed its capacity.

Most recently, emerging trends in smartphone-based methods are observed in recent literature. Manzoni et al. (2010) developed an algorithm that automatically classifies the user's transportation mode into eight classes using a decision tree. The input features were computed from the Fast Fourier Transform (FFT) coefficients of the total acceleration measured by the accelerometer [23]. A trip analysis system that consists of mobile apps and a centralized analyzer was developed to identify the travel mode and purpose of the trips sensed by smartphones, using the GPS and accelerometer [24]. It was deployed to the smartphones of the volunteers in Dubuque, IA, to serve both the volunteers and the transit agencies. Another study leveraged the same two types of sensors to classify six different travel modes in the region of Vienna, Austria [25]. Authors proposed multivariate parametric models which are fitted to the distribution of feature vectors extracted from the training set.

Very few studies employ a complete list of smartphone sensors for better classification results. Frendberg (2011) designed a smartphone app to detect transportation modes by applying a Boosted Naive Bayes classifier to data collected from GPS, accelerometer, orientation, and magnetic sensors [26]. However, the data were collected from a single user and only two travel modes, walk and automobile, were considered in that study. Another recent attempt collected multi-modal travel data in New Delhi, India, from a variety of sensors, including accelerometer, linear acceleration, gyroscope, orientation, magnetometer, light intensity meter, proximity, sound level and GPS [27]. They focused on two-wheeler and three-wheeler classification with threshold based heuristic. However, no pedestrian, cyclist, or subway is considered in that work.

3. Approaches for Travel Mode Identification

In this section, we present our approach of using mobile phone sensors to detect travel modes. It contains the details in data collection and description, sensor selection and feature selection.

3.1 Sensors and Data Description

The latest Android phone contains many powerful sensors, e.g. motion sensors like gyroscope, acceleration, gravity sensor; position sensors like GPS, magnetic field sensor, proximity sensor, and environment sensors like barometer, light sensor, ambient temperature sensor, etc. [1]. Although the potential information from these sensor readings is rich and diversified, we choose several sensors that are key important to our goal of travel mode detection: accelerometer, gravity sensor, magnetic field sensor, barometer, and light sensor. In the following subsection, we introduce each sensor and its importance to our detection task.

Accelerometer. Accelerometer readings return the acceleration as measured along each axis of the cellphone (Fig. 1), e.g., one reading is a vector: $A = < x, y, z >$.

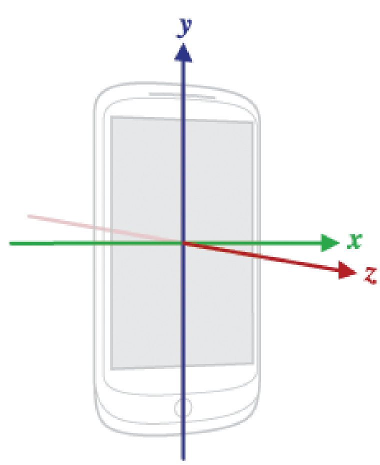

Fig. 1 The Android Phone Axes [28]

Acceleration data is an important reference to detect the pattern of the user's body movement. The 3D movement can be quantified by the acceleration along the phone's three axes. Fig 2 shows a sample plot of accelerometer readings along the Y axis for a walking user, and for a bus-riding user. The data is captured when the user holds the phone vertically. We can see that there are obvious fluctuations in Y-acceleration during walking (the red curve), while on the bus, the phone is relatively still along this axis (the blue curve).

In fact, the main difference between the two travel mode patterns on acceleration can be generalized to the difference between wheelers travel and non-wheelers travel modes. When people are traveling by bus, car, subway, they are basically sitting or standing. In such activities one's phone moves less drastically than when one is walking or jogging. Acceleration data can capture this difference and is thus used to detect the wheelers/non-wheelers travel mode as the first layer in our hierarchical classification.

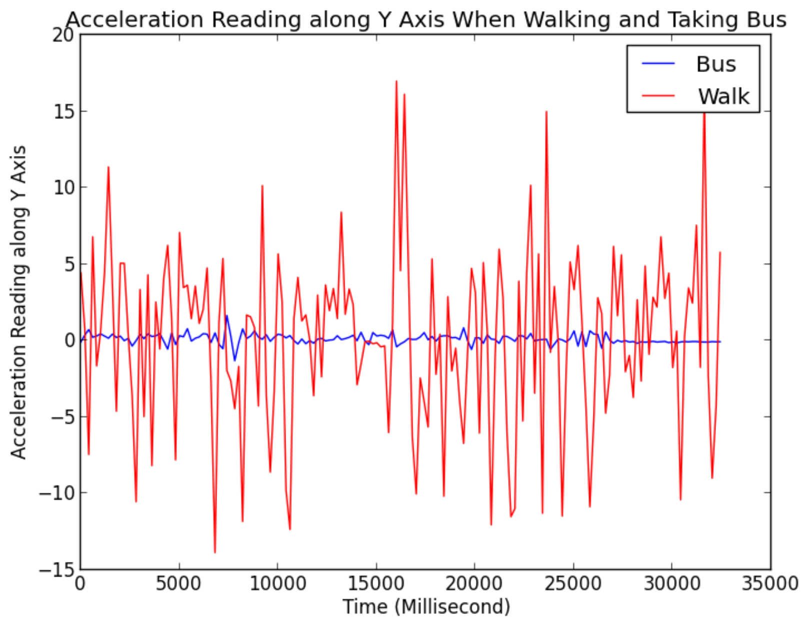

Fig 2. Acceleration Reading along Y Axis (vertical to earth) When Walking and on Bus

Gravity Sensor. Gravity sensor readings return the gravity as measured along each axis of the cellphone, e.g., each reading is a vector: $G = < x, y, z >$. If a phone is held vertically with the phone's screen facing the user, the reading would be $< 0{,}9.8{,}0 >$. Gravity sensor readings are used in conjunction with magnetic field readings to convert the accelerometer readings from the phone's coordinates to the earth's coordinates (Y axis pointing up, and Z axis pointing north). We have to do this conversion because we can't control how people hold their phones in real applications and especially during data collection experiments. In this way we reduce the noise on acceleration caused by the phone's orientation.

Barometer. Barometer reading returns the detected ambient air pressure in the unit of *hPa*. In [29], Muralidharan et al. conducted an experiment showing that the pressure detected by the smartphone barometer would change with the building structure and type, and such a pattern is learnable. In our experiment, we also verified that the barometer reading is discriminative with different transportation tools. Fig.3 presents the pressure recording by different users that are asked to take the bus, subway and car travelling at the same time. We can see that during the 7000 readings along 30 minutes, the pressure inside the train is the most stable one. Bus is fluctuated within a certain range. The pressure in the car is changing drastically. One explanation for this lies in the size of the cart where the air pressure is detected for each transportation tool. The cart of the train is the biggest among the three, thus it has a more stable pressure. Contrarily, vehicles have the smallest closed space (most of the time people keep the window closed), small changes such as A/C system on the car would be reflect on the air pressure and lead to bigger fluctuation in reading. Another reason that might be related is that most of the time subways run underground, where the environment is less effected by other facts like heavy traffic, dense crowd, windy weather, etc. Compared with the previous two environments, the bus cart is middle sized and its inside environment is between trains and cars. Pressure data is used in our second level classification, i.e., the wheelers travel mode detection.

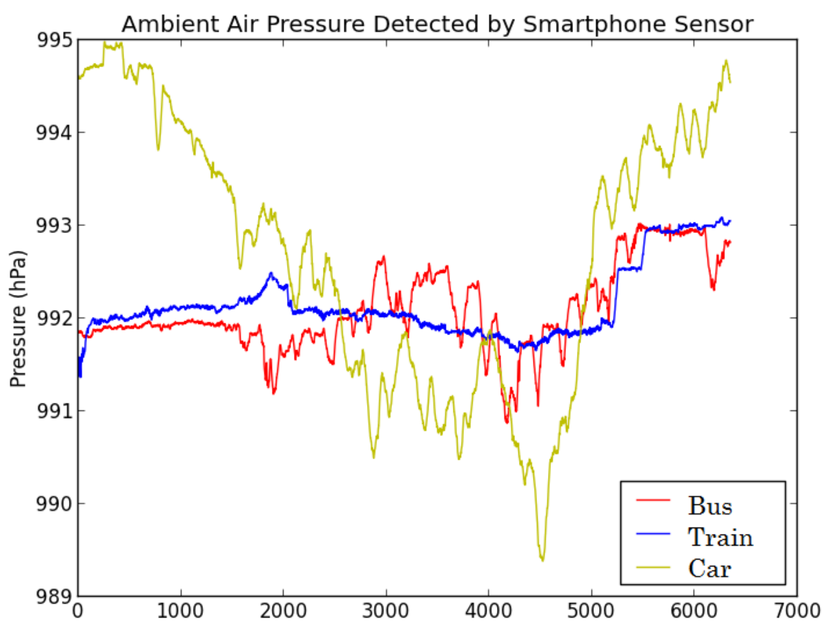

Fig. 3 Air Pressure Detected on Different Transportation Tools.

Light Level. The light sensor reading returns detected ambient illumination in the unit of *lx*. Similar to the pressure data, light level is also an important factor to differentiate the transportation tools. Fig. 4 is the light level detected while different users are asked to take a bus, subway and car travel at the same time. Because the passenger seat in the car is in a lower position and it travels faster, even passing by a truck would make the light level change. This can explain why the light level inside a car is changing more than the other two. However, the light level detected by cellphone would also depend on where the user puts the phone. A phone inside a bag or the pocket is definitely different from a phone that is being held in hands in terms of the light sensor readings. We will discuss this issue in the experiment part.

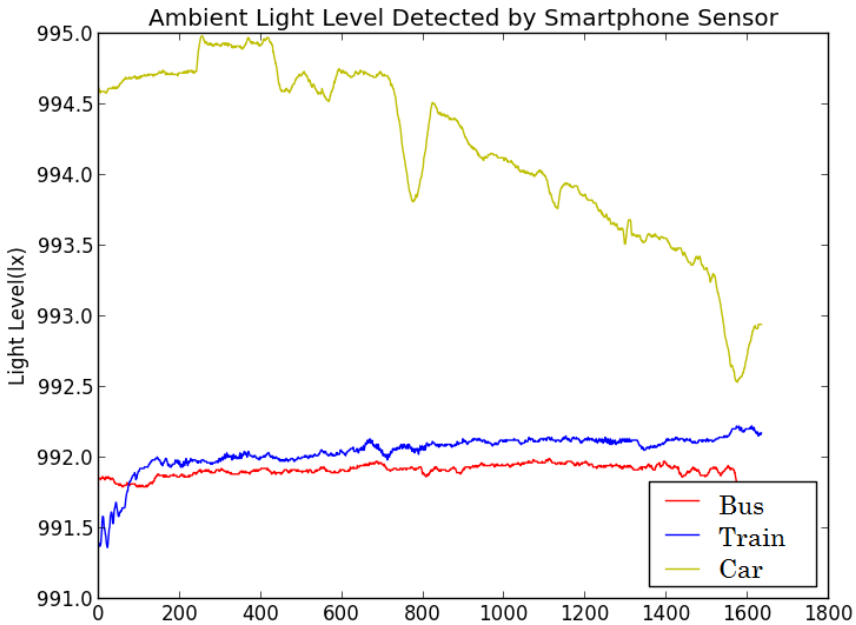

Fig. 4. Ambient Light Level Detected by Light Sensor.

Magnetic Field Sensor. The geomagnetic field sensor detects the environment's geomagnetic field strength along the smartphones' three axes, e.g. one reading is a vector: $M = < x, y, z >$. Magnetic field strength can be impact by the object in the environment's (e.g. the one with hard iron like magnetized iron, steel, etc.), which may imply the phone's environment. During our experiment we find that the magnetic field sensor reading showing a much higher fluctuation on the subway, which is due to the material of the subway car body, the electricity power for the train, and other factors from the track. Fig. 5 shows the magnitude square change of magnetic field along travel time on subway, bus and car, respectively. This finding helps us distinguish the mode of traveling with subway.

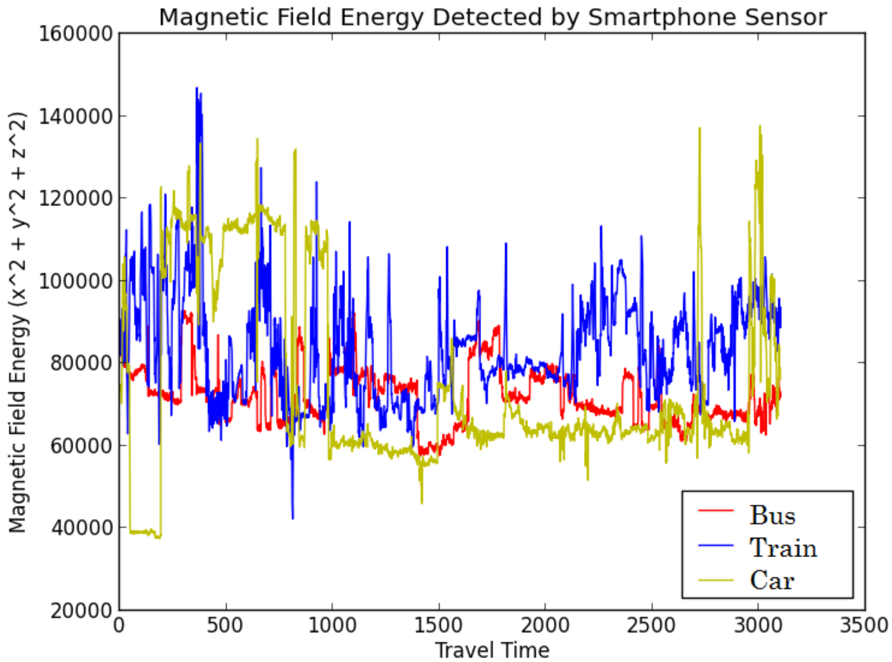

Fig. 5 Magnetic Field Magnitude Square Detected on Different Transportation Tools

3.2 Classification

In this section, we present how the feature vector is computed and how the classification model is built.

3.2.1 Feature Extraction

The sensors were set to 5Hz for the sampling rate. Raw data collected from the sensor was segmented with a window size of 64, e.g. 64 readings for one segment, which is around 13 seconds' in travelling. This window length was chosen for the best classification outcome of the frequency domain feature calculation. The raw data based on the phone's coordination system was then converted into orientation independent data using gravity and magnetic field information. In feature computation, we computed both the time domain features and the frequency domain features with different sensors. The time domain features include Max, Min, Standard Deviation, Mean and Magnitude of each reading vector along the three axes. The frequency domain features were extracted based on the Fast Fourier Transform results. The features contain the energy, offset, main frequencies, and histogram of the normalized frequencies. Table 1 summarizes the extracted features and the corresponding descriptions.

Table 1 Features Extracted for classification

Features	Descriptions	Sensors
$Max\_x_a, Max\_y_a, Max\_z_a$	Maximum of acceleration reading on x, y, z axis	Accelerometer
$Min\_x_a, Min\_y_a, Min\_z_a$	Minimum of acceleration reading on x, y, z axis	Accelerometer
$Mean\_x_a, Mean\_y_a, Mean\_z_a,$ $Mean_{pressure}, Mean_{light}$	Mean of pressure reading, light reading and acceleration reading on x, y, z axis	Accelerometer, Pressure, Light
$STD\_x_a, STD\_y_a, STD\_z_a,$ $STD_{pressure}, STD_{light},$ $STD_{magnetic\_magnitude}$	Standard Deviation of the pressure reading, light reading, acceleration reading along x, y, z axis, magnitude square of magnetic field along 3 axes $(x_g^2 + y_g^2 + z_g^2)$	Accelerometer, Pressure, Light, Magnetic Field Sensor
$Offset\_x_a, Offset\_y_a, Offset\_z_a,$ $Offset_{Magnetic}$	Offset of DFT on x, y, z axis acceleration and magnitude square of magnetic field along 3 axes	Accelerometer, Magnetic Field Sensor
$Energy\_x_a, Energy\_y_a, Energy\_z_a$ $Energy_{magnetic}$	Energy of DFT ($\sum_i (real_i^2 + image_i^2)$) on x, y, z axis acceleration, and magnitude square of magnetic field along 3 axes	Accelerometer, Magnetic Field Sensor
$X_{a_0}, X_{a_1}, \dots, X_{a_9}$ $Y_{a_0}, Y_{a_1}, \dots, Y_{a_9}$ $Z_{a_0}, Z_{a_1}, \dots, Z_{a_9}$ $Mag_0, Mag_1, \dots, Mag\_9$	Histogram of normalized DFT of acceleration on x, y, z axis and magnitude square of magnetic field along 3 axis	Accelerometer, Magnetic Field Sensor
$Freq_{x_a}[0,1,2,3]$ $Freq_{y_a}[0,1,2,3]$ $Freq_{z_a}[0,1,2,3]$ $Freq_{magnetic}[0,1,2,3]$	The top 4 frequencies of acceleration on x, y, z, and magnitude square of magnetic field	Accelerometer, Magnetic Field Sensor

3.2.2 Classification Models

We use a hierarchical model for the classification. Intuitively, we know that the six travel modes (buses, subways, cars, walking, and jogging) are quite different in terms of the cellphone's moving (fluctuation) patterns. People inside buses, subway, cars or riding a bike are more likely to be still while people walking or jogging have a relatively higher body movement, which would reflect on the cellphone's acceleration data. We use this observation to construct our hierarchical classification model, that is, we first train a model solely based on the acceleration features to classify whether it belongs to the wheelers transportation mode (bus, car, subway, bike) or the non-wheelers transportation mode (walking, jogging). Then within each group, we involve more features from other sensors such as pressure, light for the detailed travel mode detection. Fig 6 shows the structure of our hierarchical classification model.

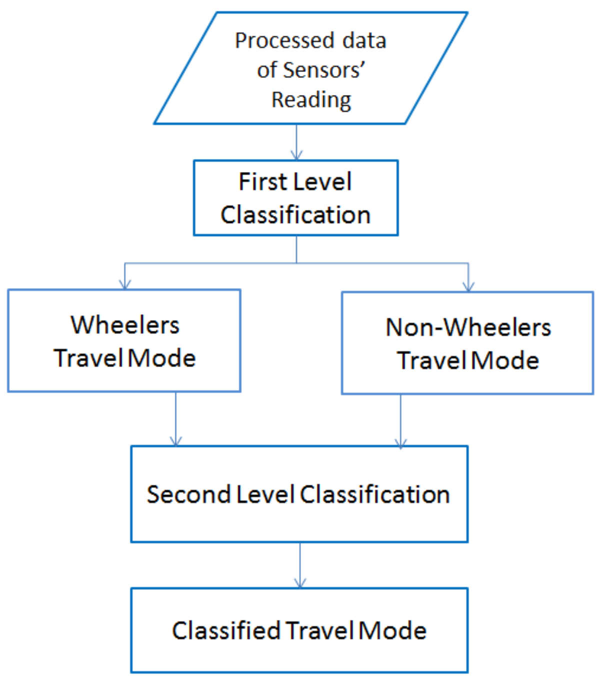

Fig. 6 Hierarchical Classification Model for Travel Mode Detection

The First level classifier is a binary classifier that only takes acceleration features as its inputs. It classifies the travel mode into wheelers travel mode and non-wheelers travel mode. Then inside each subgroup, a second level classifier is applied. For the non-wheelers travel mode, the leading features are still extract from acceleration data. For the wheelers travel mode, we combine the feature vectors calculated from all sensors' data for classification.

3.3 Experiment

This section presents the system details, including the smartphone models to collect data, the data details, and the experiment results, followed by some discussions.

3.3.1 System Details

We have chosen Android-based cell phones as our platform for data collection. The well-known advantages of Android operating system are free, open source, easy to program, and it is dominating the smartphone market. Another important reason for us to adopt Android system is that some of the latest android phones like Google Nexus 5 and Samsung Galaxy 4 are equipped with the advanced sensors such as barometer and light sensors. Data readings from these sensors are important in our approach. In our experiment, we use Samsung Galaxy 4, 5.

The main goal of our application is to record the sensors' reading while the user is in certain travel mode. We collect the raw data for each of the travelling modes. The recorded data are assigned an anonymous ID and then sent to the server for further process. The server side program has two main tasks: (1) data storage for the future use; and (2) data analysis including model training and travel mode classification.

3.3.2 Data Details

Our data was collected by six volunteers living in Buffalo NY in July, 2014. Each of them is assigned some travel tasks with one or more travel modes. They all traveled along Main Street with different directions and different modes, between South Campus of University at Buffalo and downtown. Volunteers were asked to record their true travel mode by selecting the corresponding options, shown as Fig. 7. In order to avoid the specific traffic pattern within certain hours, and the time-of-day effect on the environment air pressure and ambient light, we made the control on the experiment time. On one hand, the experiment last for six hours in total and different batches of data are recording at early afternoon, late afternoon in rush hours and evening, respectively. On the other hand, the subjects that in different traffic modes are required to record the data at the same time for each data batch.

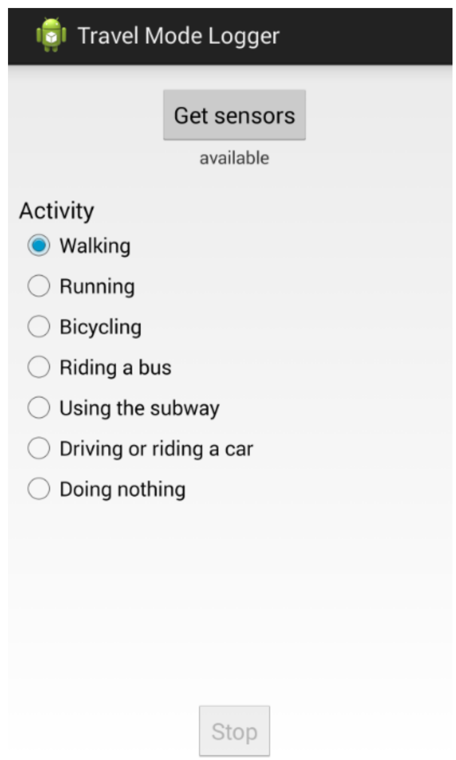

Fig. 7. The Android App developed for travel data collection

3.3.3 Experiment Results

We conducted our data analysis using Weka [30] with a 10-fold cross validation. The result shows a promising result in terms of the classification accuracy. The binary classification in the first layer gets 100% accuracy with both Bayes Net and Decision Tree methods. In the second layer classification, the *walk/jog* group gets 98.1% accuracy on cross-person test and 100% with the single subject. The wheeler travel mode classification gets 96.42% as the highest accuracy using Bayes Net. Table 2 summarizes the detailed results, and Table 3 presents the confusion matrix.

Table 2 Precision and Recall Accuracy Detail

	Precision Accuracy				Recall Accuracy			
	Bayes Net	Naïve Bayes	Random Forest	Decision Tree	Bayes Net	Naïve Bayes	Random Forest	Decision Tree
Train	95.8%	75.8%	80.4%	75%	90.2%	50%	88.2%	76.5%
Bus	100%	74.1%	90%	82.7%	99%	87.8%	91.8%	87.8%
Car	89.8%	61.1%	84.6%	76.2%	97.8%	73.3%	73.3%	71.1%
Bike	100%	100%	100%	100%	100%	100%	100%	98%
Walk	100%	/	/	98%	100%	/	/	98%
Jog	100%	/	/	100%	100%	/	/	100%
Average	96.4%	78.3%	88.8%	88.7%	97.8%	77.5%	88.8%	88.6%

Table 3 Confusion Matrix

Classified As ->	Bus	Train	Car	Bike	Walk	Jog
Bus	94	2	0	0	0	0
Train	0	84	18	0	0	0
Car	2	10	78	0	0	0
Bike	0	0	0	100	0	0
Walk	0	0	0	0	99	0
Jog	0	0	0	0	0	78

3.3.4 Discussions

We can see that car mode has the lowest accuracy. Also among all travel modes train and car are the two categories with highest misclassification rate, and most of the mislabeled instances are confused with each other. One possible explanation is that in central business area, low speed and acceleration/deceleration for car mode are similar with trains. We believe this type of misclassification can be further rectified by a simple map match.

As is mentioned in the previous section, the light level would depend on where user keeps the phone. Although a user who is attaching to his/her phone would be more likely to have the phone on hand, while someone who tends to read books on the subway would more often have a phone inside the pocket or in the bag. This kind of behaviors' pattern is not easy to learn. In order to see how important the light feature is in our method, we compare the accuracy that with light feature and without light features using Bayes Net. The precision drops from 96.4% to 90.3%. Nonetheless, an accuracy of 90.3% without the light feature is still acceptable in some applications.

Other sensors such as barometer and magnetometer are also highly related to the environment status. This raises a question that does our model only fit the city of Buffalo traffic mode in certain season? Or could it be generalized to the urban transportation? We would put more effort in answering this question in the future research.

4. Conclusions

In this paper, we propose a real-time and network- free method to detect a user's travel mode using smartphone sensors. Our application is built on the latest Android smartphone with multimodality sensors. By carefully designing the time domain and frequency domain features; together with a hierarchical classification model, we achieve 100% accuracy in a binary classification wheelers/non-wheelers travel mode, and an average of 96.4% in all the six travel modes. Future work includes (1) the generalization of the classification model to detect more complicated travel model (e.g., Federal Highway Administration's 13 different vehicle classes), (2) group feature selection to identify the best sensor data to use for both high accuracy of travel mode identification and low energy consuming, and (3) implementation of such approach for mass travelers on smartphones.

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