Probabilistic multi-modal map matching with rich smartphone data

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Abstract

The conventional map matching algorithms identify from a GPS trace the true uni-modal path, which is a path with a single transport mode. There are also studies on detecting transport modes from GPS data. A recent study on probabilistic map matching shows that knowing the transport modes helps in identifying the true paths. It is also obvious that knowing the physical paths improves the detection of transport modes. E.g. known that the GPS points are on train tracks, it is overwhelmingly likely that the corresponding transport mode is train. In this paper, we aim at developing a model for identifying multi-modal paths. In this model, the transport modes and physical paths are detected simultaneously in order to take advantage of the correlation between them. In this model, many kinds of data from smartphone are fused to improve the accuracy of the detection result. Those data include GPS, nearby Bluetooth and acceleration. The model doesn't require pre-processing of raw data into segments with single transport modes. The problem is modeled in a probabilistic manner such that error in measurements can be accounted for. The modeling methodology is to simulate the process of the smartphone user traveling on a path while the smartphone is recording the measurements by using travel models to capture the traveling and measurement models to capture the recording.

Keywords

multi-modal map matching, transport mode detection, smartphone data, GPS data

1 Introduction

GPS capable devices have been harnessed in travel related surveys , to replace conventional methods such as travel diaries and prompted recall questioning (e.g., Murakami and Wagner, 1999; Bricka and Bhat, 2006). Nowadays, smartphones embed not only GPS chips, but also other sensors and functionalities which provide richer information about the carriers' context. Therefore, we propose, as in Stopher (2008); Bierlaire *et al.* (2010), to utilize smartphones as travel survey tools. The richness of available data from the smart phone offers good opportunities for modeling travel behavior. However, in order to harness the advantages of the smart phone data, new models need to be developed to bridge the gap between observed data and behavior models.

The transport mode and the physical path are two main aspects of user's travels. The identification of mode and path from GPS data has drawn a lot of attentions in transport research (e.g., Schuessler and Axhausen, 2009a,b; Liao *et al.*, 2007a). The traditional methods, which infer a complete multi-modal trip from a GPS track, contain 3 stages. Firstly, a GPS track is deterministically divided into several single-mode segments by detecting change points or walk segments. Then, transport mode inference algorithms (e.g., Reddy *et al.*, 2009) are applied to each segment to identify its transport mode. Thirdly, map matching (MM) algorithms (see Quddus *et al.* (2007) for a comprehensive review) are applied to detect the physical path of each segment. The first and most serious problem in that procedure is that the deterministically detected change points or walk segments may be wrong. Consequently, the inference result will be definitely wrong. For example, if a real change point is not detected, two segments with two different transport modes will be considered as one single segment with one single transport mode.

In this paper, we propose a modeling framework that identifies the physical paths and transport modes simultaneously in order to take advantage of the correlation between them, and measures that probability that the recorded smartphone data are generated. It extends the probabilistic map matching method proposed by Bierlaire *et al.* (2010) to multi-modal case, therefore we term it as multi-modal map matching method. A multi-modal path is a physical path with associated transport modes in the transport network. Each location on a path contains two aspects of information: the coordinates and the transport mode. Figure 1 illustrates a multi-modal path with 3 mode segments from the origin O to the destination D. We measure the likelihood that the smartphone data are observed by modeling the process that the smartphone user travels on a path while the smartphone is recording measurements. Travel models are used to capture the traveling and measurement models are used to capture the recording process respectively.

MM algorithm usually uses GPS coordinates, and transport mode detection uses speed and ac-

Figure 1: Network representation of a multi-modal path

Table 1: Mobility relevant data and sampling interval.

Type	Interval (second)	Remark
GPS	10	GPS fix.
BT	180	Nearby Bluetooth devices.
SYS	60	System information, e.g. charging status, phone interaction.
WLAN	120	Nearby WIFI spots.
GSM	60	Connected GSM cell.
ACCEL	120	Measurements from accelerometer.

celeration. However, to the best of our knowledge, no study fuses many kinds of smartphone data to detect modes and paths simultaneously. The proposed modeling framework is capable to fuse various kinds of data. And the availability of more data increases the accuracy of the results. Different smart phone models have different sets of built-in sensors with different performances. In the future, new sensors, with different level of accuracy, will be made available. The developed method are flexible to availabilities, precisions and accuracies of the data. The flexibility also means that the precision of the results should increase with the availability of more numerous or more accurate data.

2   Data collection and analysis

2.1   Data collection

A large scale smartphone data collection campaign has been launched in September 2009 by Nokia Research Center in Lausanne, Transp-or Laboratory at EPFL, and IDIAP Switzerland. In this campaign, a sample of about 180 individuals have volunteered to carry with them a smart phone that automatically collects a great deal of raw data from their sensors and applications. Various pieces of data are collected from the built-in sensors and software. Each participant is planed to be involved for 2 years. Table 1 summarizes the kinds of data that is relevant to mobility information and their sampling intervals. The phone interaction event in "SYS" data indicates whether or not, in the past 60 seconds, a phone interaction was triggered by the user. Among them, the GPS data is the most important mobility relevant information, and has been studied extensively in transport literature for mobility detection (e.g., Liao *et al.*, 2007b; Quddus *et al.*, 2007; Bohte and Maat, 2009).
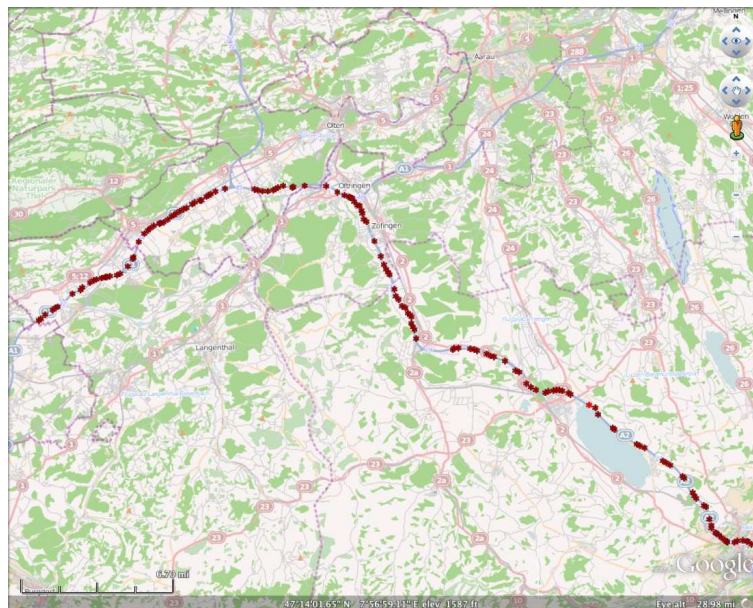
(a) Charts.

(b) GPS on map.

Figure 2: Smartphone data collected from trip 1.

2.2 Data analysis

In order to get more insights from the data, we analyze two sets of smartphone data collected from two different trips. The data are visualized on Figure 2 and 3 respectively. Numeric values are shown on the charts, and GPS coordinates are shown on maps as red stars. In the charts, the x-axis is time which is formatted as "Day of the week and hour of the day". For instance, "Mon 14" means 14:00 on Monday. A point in the last chart indicates a phone event; for example, a
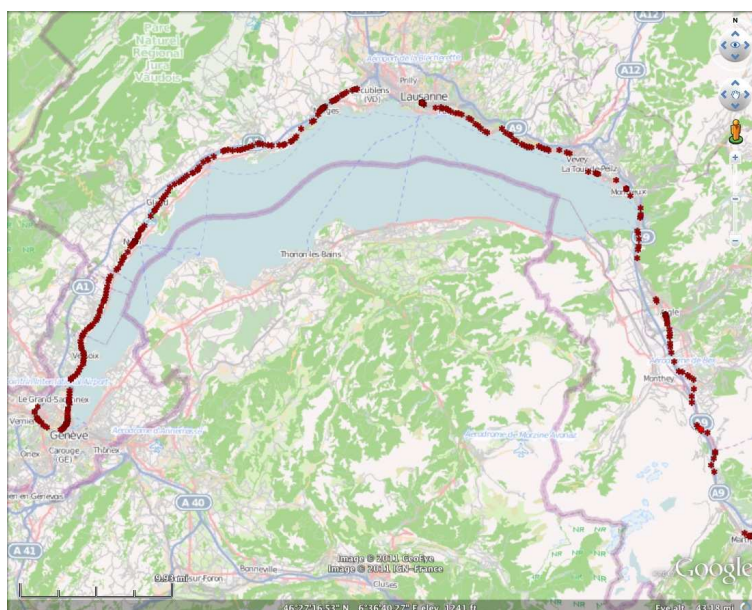
(a) Charts.
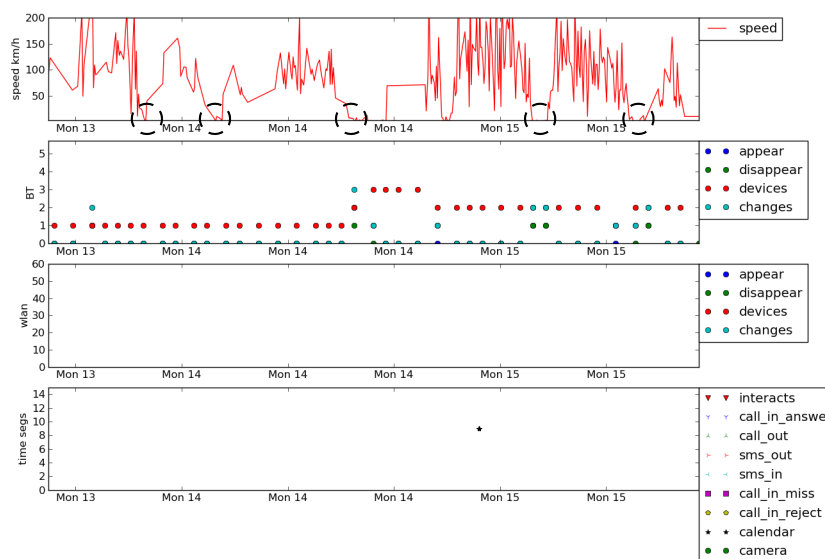
(b) GPS on map.

Figure 3: Smartphone data collected from trip 2.

black star shows a calendar entry at the corresponding time.

We aim at inferring the transport modes and paths of the trips using the following logic:

- Speed. The speed data of both trips are around $100km/h$. Therefore, they are over-whelmly likely to be motor-based mode.
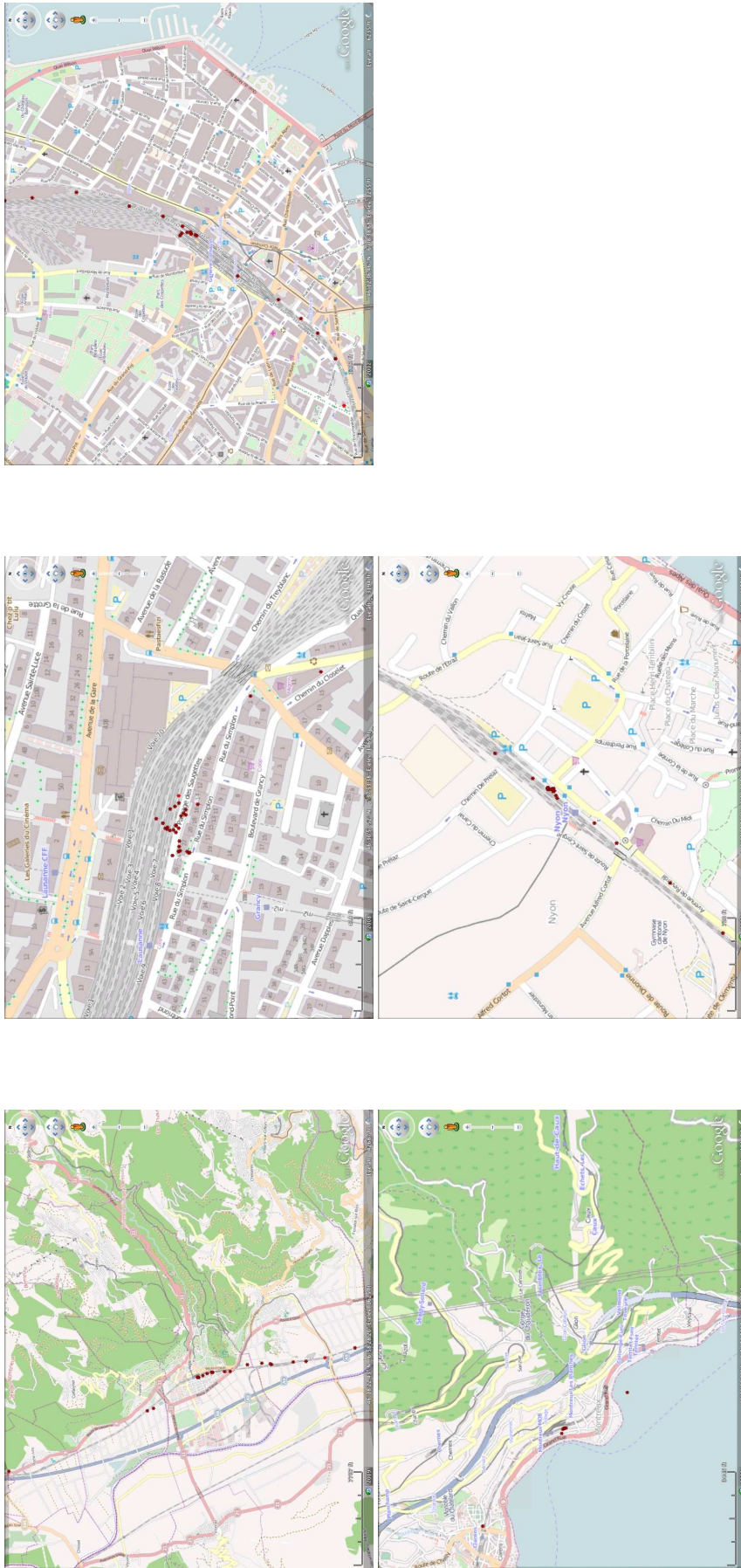
Figure 4: Stops observed from trip 2.

- GPS points of trip 1 are very close to and consistent with a highway. While GPS points of trip 2 are more likely to be recorded from train tracks nearby, especially, we observe 5 intermediate stops (clouds of GPS points) nearby train stations (shown in Figure 4). These stops are consistent with the low speed values indicated on the speed chart in Figure 2(a) So it is very likely that trip 1 is a car trip, while trip 2 is a train trip and their paths are the nearby highway and train tracks respectively.
- In trip 1, there is only one BT devices nearby, and it doesn't change for the entire trip. But in trip 2, there are more BT devices, and they change (appear or disappear) while the GPS points are near the train stations. In fact BT devices are mostly embedded on personal mobile devices, e.g. mobile phones and laptops, hence they can represent their carriers. And in reality, due to the capacity, there are usually very few people in a car, and they stay for the entire trip, while a train cabin can accommodate many people and they go on-board or off-board at train stations. This BT information further increase our confidence on the inference of their transport modes.
- Other data tell little information.

From the above inference process, we conclude three types of useful information from the smartphone data, speed value, GPS coordinates, and number of nearby BT devices. Moreover, since people usually charge the battery at home, at work, or in their cars, the charging status also contain mobility information. WLAN and GSM also contain location information since their positions are fixed, but the availability of their location information varies. Acceleration is also a very important aspect of the characteristics of transport modes, and it will be discussed in Section 5.

3 Probabilistic multi-modal map matching

In this section, we propose a method that measures the likelihood that a sequence of smartphone observations is recorded while the carrier is traveling on a multi-modal path. This method is a generalization of a probabilistic uni-modal MM method developed by Bierlaire *et al.* (2010).

3.1 Notation

- p, a multimodal path;
- $x \in p$, a location on path p;
- m, the transport mode associated with x;
- y_i, a measurement recorded at times t_i;
- $y_{1:T}$, a sequence of measurements recorded at time $\{t_1, \ldots, t_T\}$.
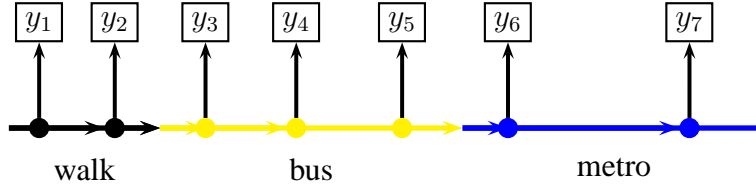
Figure 5: Graphic representation of the problem.

3.2 Measurement equations

We now derive the probability that a given path p generates the data $y_{1:T}$:

$$\Pr(y_{1:T}|p) \tag{1}$$

It is a recursive process:

$$\Pr(y_{1:T}|p) = \Pr(y_T|y_{1:T-1}, p)\Pr(y_{1:T-1}|p) \tag{2}$$

We assume that time is recorded without error. Therefore, $x_k \in p$ is denoted as the corresponding location where y_k is observed at time t_k. Hence, at each iteration k the following probability is calculated:

$$\Pr(y_k|y_{1:k-1}, p) = \int_{x_k \in p} \Pr(y_k|x_k, y_{1:k-1}, p)\Pr(x_k|y_{1:k-1}, p)dx_k. \tag{3}$$

The first term in Eq 3,

$$\Pr(y_k|x_k, y_{1:k-1}, p) = \Pr(y_k|x_k, p), \tag{4}$$

models the measurement error of the device. The second term predicts the position at time t_k of the traveler. It is written as:

$$\Pr(x_k|y_{1:k-1}, p) = \int_{x_{k-1} \in p} \Pr(x_k|x_{k-1}, p)\Pr(x_{k-1}|y_{1:k-1}, p)dx_{k-1}. \tag{5}$$

The first term $\Pr(x_k|x_{k-1}, p)$ is the travel model that captures the user's movement and will be discussed later. The second term $\Pr(x_{k-1}|y_{1:k-1}, p)$ is the posterior distribution of the true location at time t_{k-1}, and can be derived easily from Bayes rule with reasonable simplifications:

$$\Pr(x_{k-1}|y_{1:k-1}, p) = \frac{\Pr(y_{k-1}|x_{k-1}, p)}{\int_{x_{k-1} \in p} \Pr(y_{k-1}|x_{k-1}, p)}. \tag{6}$$

The model can be graphically shown with an example in Figure 5, in which there is a given path p and a sequence of 7 observations $y_{1:7}$. Solid points are the unknown true location x_k for each corresponding measurement y_k and the arrows denote the dependencies between variables. It is very easily noticed from the graph that there are two types of dependencies. First, each location x_k on path depends on the previous location x_{k-1}; second, each measurement y_k depends on the location x_k. They accord with the travel model $\Pr(x_k|x_{k-1}, p)$ and the phone measurement model $\Pr(y_k|x_k, p)$.

4   Travel model

As introduced in (Bierlaire *et al.*, 2010), the travel model is used to predict the position of the smartphone over time. More precisely, it predicts the position x_k of the device at time t_k if the position at time t^{k-1} is x^{k-1}, and the device is traveling on path p. There are several ways of implementing the travel model, for example, traffic simulator or real-time traffic information. However, due to their complexities, in this paper, we extend the simple analytical method proposed in (Bierlaire *et al.*, 2010) to multi-modal context.

We assume that transport modes can be characterized by their speed profiles. For instance, a speed distribution for car mode is estimated in Bierlaire *et al.* (2010). In this paper, we deal with multi-modal case with several different modes, and denote $f_v^m(\cdot)$ for the speed distribution of transport mode m. The speed characteristics have been studied in the literature for different transport modes. For examples, Knoblauch *et al.* (1996) estimate average and 15th percentile walking speed from a field study; Thompson *et al.* (1997) estimate the mean and the standard deviation of biking speed. Bierlaire *et al.* (2010) calibrated the speed distribution for car travel. Bus, metro, and train lines information can be integrated for the estimation of public transit. In this paper, speed distributions are estimated from observed speed data for 6 transport modes walk, bike, car, bus, metro and train. .

Following Bierlaire *et al.* (2010), we assume a mixture of a negative exponential distribution and a log normal distribution for a speed distribution. The first is designed to capture the instances where the traveler is stopped at intersections, public transit stops, or traveling at low speed before or after that stop. The second is designed to capture the traveler moving at regular speed. In practice, we found a mixture of negative exponential and normal fits better for walk.

mode	data amount	w	λ	μ	σ
bike	7675	0.40	0.10	2.90	0.31
bus	674	0.45	0.15	2.95	0.53
car	1213	0.18	0.17	3.68	0.61
metro	246	0.53	0.12	3.40	0.42
train	340	0.27	0.17	4.52	0.54
walk	1262	0.36	0.17	5.08	2.21

Table 2: Parameter estimates of speed distributions

The distributions is

$$f_v(v) = w\lambda \exp^{-\lambda v} + (1-w)\frac{1}{\sqrt{\pi\tau^2}} \exp^{-\frac{(v-\mu)^2}{2\tau^2}}, \tag{7}$$

for walk, and is

$$f_v(v) = w\lambda \exp^{-\lambda v} + (1-w)\frac{1}{v\sqrt{\pi\tau^2}} \exp^{-\frac{(\ln v-\mu)^2}{2\tau^2}}, \tag{8}$$

for other modes. The parameters to be estimated are:

- w, the weighting;
- λ, the scale parameter of the negative exponential distribution;
- μ, the location parameter of the log normal distribution;
- τ the scale parameter of the normal/log normal distribution.

Figure 6 shows the normalized histograms of the recorded speed data and the estimated speed distributions. Table 2 reports the parameters estimated by maximum likelihood, as well as the amount of data that are used for the estimation.

Since we are dealing with multi-modal path, we need to consider a situation that for a specific x_k, $m_k \neq m_{k-1}$, and there are change points from x_{k-1} to x_k on path p. For illustration purpose, we assume here that there is one known change point x_c (it is easy to extend to more general cases that there are more than one change point). The travel from x_{k-1} to x_c has a single mode m_{k-1}, and travel from x_c to x_k has another single mode m_k. Since time is assumed to be measured without error, therefore the travel model $\Pr(x_k|x_{k-1}, p)$ is equivalent to:
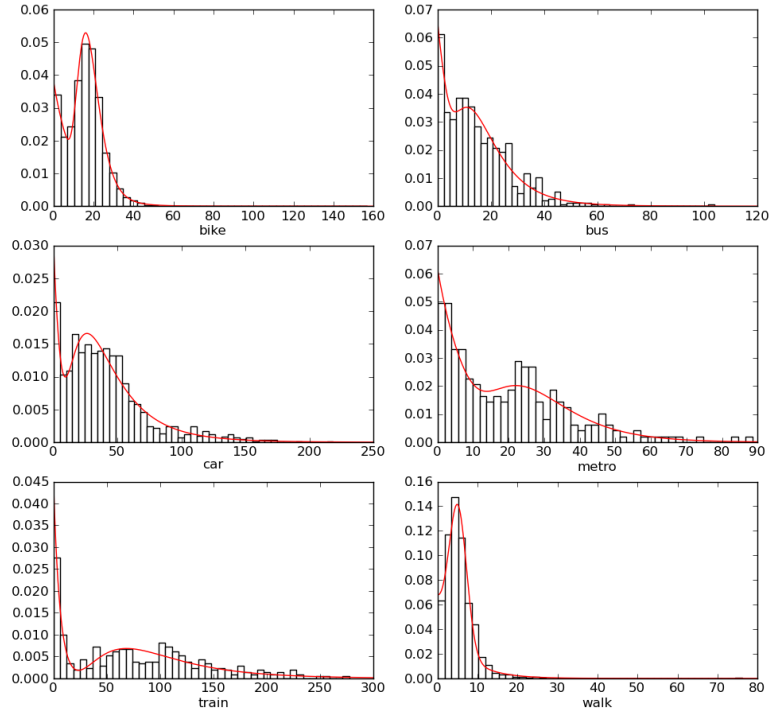
$$\Pr(x_k|x_{k-1}, t_{k-1}, t_k, p). \tag{9}$$

Figure 6: Speed distributions of 6 transport modes.

Let t_c denotes the random variable that the traveler arrives at x_c, Eq 9 equals to

$$\Pr(x_k|x_{k-1}, t_{k-1}, t_k, p) = \int_{t_c=t_{k-1}}^{t_k} \Pr(x_k|x_c, t_c, t_k, p) \Pr(x_c|x_{k-1}, t_{k-1}, t_c, p) dt_c. \tag{10}$$

Following Bierlaire *et al.* (2010), we can write Eq 10 as

$$\int_{t_c=t_{k-1}}^{t_k} f_v^{m_k}\left(\frac{d_p(x_c, x_k)}{t_k - t_c}\right) f_v^{m_{k-1}}\left(\frac{d_p(x_{k-1}, x_c)}{t_c - t_{k-1}}\right) dt_c, \tag{11}$$

in which $d_p(\cdot)$ calculates the distance of two points on path p.

The formulation for no change or more than one change between x_{k-1} and x_k can be easily generalized from the above discussion. And we also recommend to read Bierlaire *et al.* (2010) for detailed discussion about no change situation.
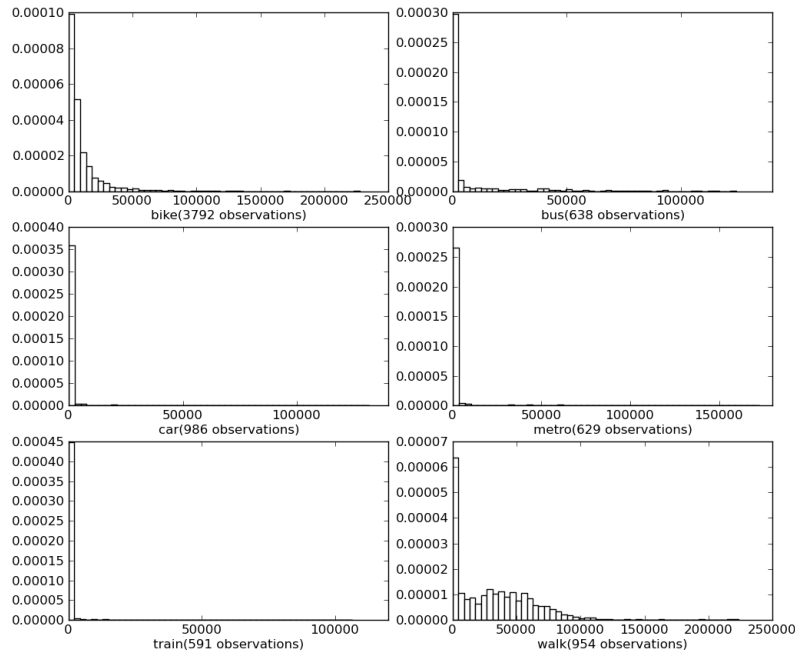
Figure 7: Histograms of accelerometer measurements.

5   Phone measurement model

This modeling framework allows to use any kind of phone measurement by using the phone measurement model Eq 4. Each location on a multi-modal path is associated with a transport mode, therefore, the phone measurement model (Eq 4) can be also written as:

$$\Pr(y_k|x_k, m_k, p). \tag{12}$$

From the formulation, we should notice that the phone measurement should contain information about the physical location x_k, or transport mode m_k, or the path p. Following the discussion in Section 2.2, we will discuss or specify the phone measurement models for the following data:

- GPS coordinates. The GPS coordinates measurement model accounts for the error in both the GPS measurement and the network data. And the model proposed by Bierlaire *et al.* (2010) is directly applicable here.
- GPS speed. The speed distribution derived in Section 4 can be used for the measurement model for speed.
- Acceleration. The measurements from built-in 3-dimensional accelerometer are also recorded periodically. The higher the value of the measurement, the higher the accel-
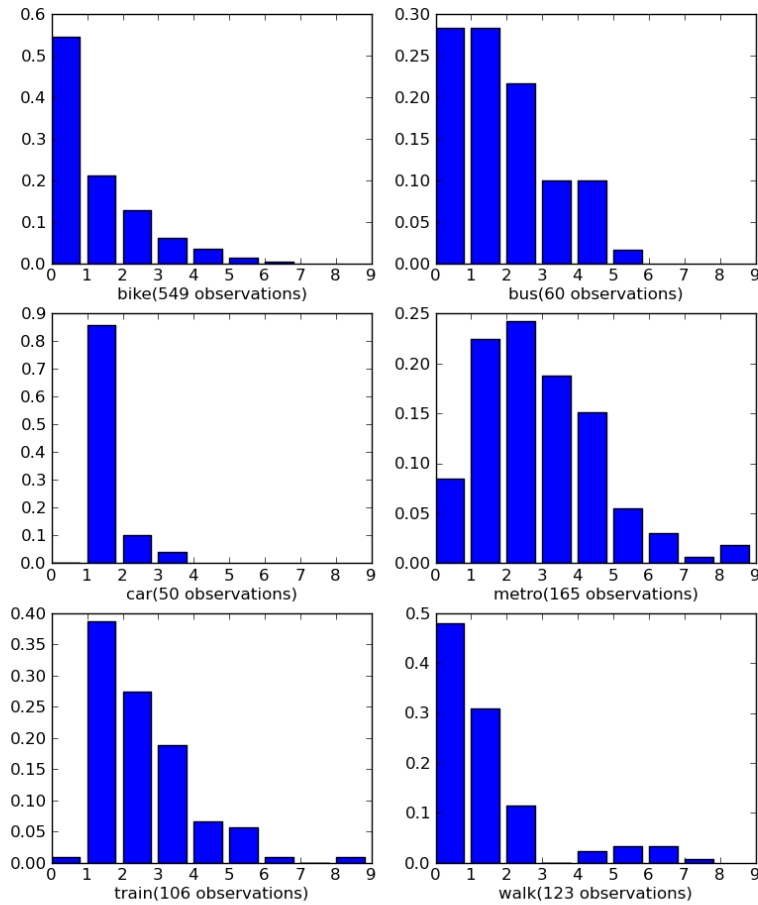
Figure 8: Relative frequency of number of nearby BT devices.

eration. The histograms of some collected measurements are plotted in Figure 7. These measurements are very noisy since the build-in accelerometer is not precise, therefore require more analysis in order to construct a measurement model. However, we can still observe some interesting phenomenons. First, most of the time, the measurements values are very low, close to zero, which means that human movements are usually smooth without too much acceleration and deceleration. Second, walk is the least smoothy because people lift the legs (hence body) all the day during walking. Third, motor-based modes are in general more stable, especially train and metro because they only accelerate or decelerate at stops/stations.

- number of nearby BT devices. As introduced in Section 2.2, this measurement indicates nearby people carrying BT mobile devices, hence, indicates the context of the transport modes. The relative frequency of some collected data is shown in Figure 8. As can be observed from the figure that in general, there are more BT devices in public transit, while less in car. Since number of nearby BT devices is a discrete variable and its support
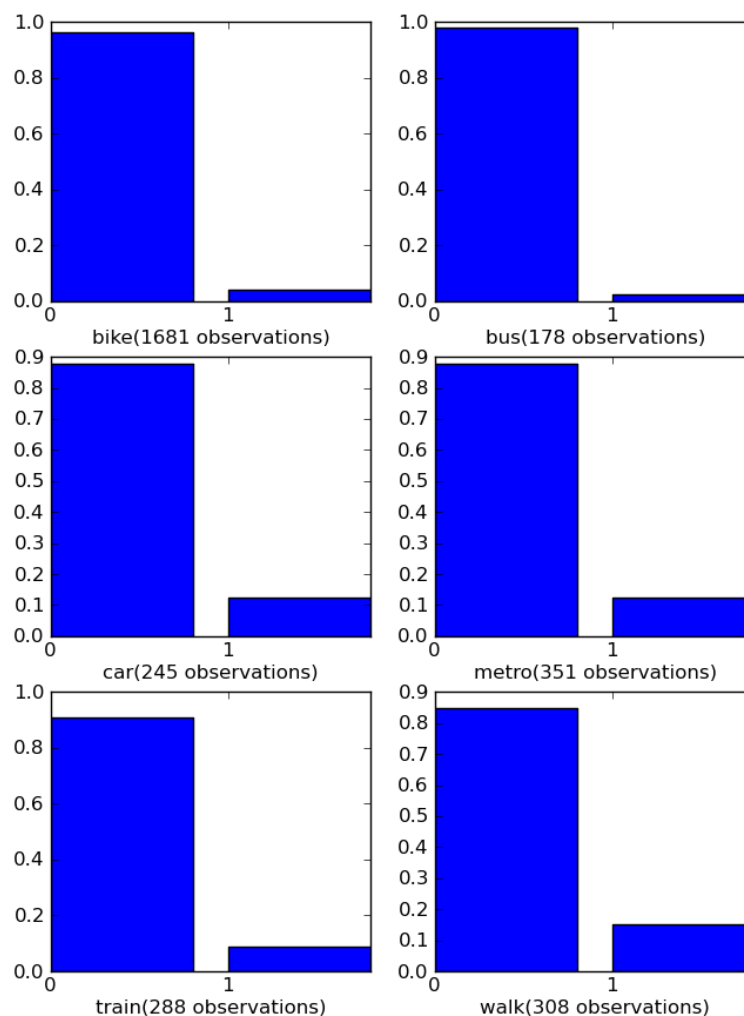
Figure 9: Relative frequency of phone interaction event.

    in practice is limited due to the range of BT signal and the capacity of the transport mode, the relative frequency can be directly used as the measurement model.

- phone interaction. The relative frequency of phone interaction indicator from collected data is shown in Figure 9. Most of the time, the user doesn't interact with the phone. The difference among different modes is not very significant. The phone interaction frequency is also individual dependent. Some people incline to interact with phone more frequent than another due to their habits. In order to find relative information, more data and study is needed.

- Charging. We don't observe any charging event during trips. However, we still believe that if charging happens, it is most likely to happen in a car.

6 Conclusions

In this paper, we propose an integrated modeling framework for measuring the likelihood that a multi-modal path generates a set of smartphone data. This method has following advantages:

- It models transport modes and physical paths simultaneously in order to take advantage of their correlation.
- It utilizes rich smartphone data, and it is extendable to account for more data which will be available in the future as mobile devices become more and more advanced.
- It models real processes of the smartphone data being recorded. A travel model is used to capture the movement of the smartphone user. And phone measurement models are used to capture the recording processes of the smartphone device.
- The probabilistic model accounts for error in the data, therefore, it is useful for behavior study.

This method is in fact a generalization of probabilistic uni-modal map matching (see Bierlaire *et al.* (2010) for details). The uni-modal map matching has been implemented and successfully applied to GPS data. Therefore, we will extend the software package for the method proposed in this paper, and will apply it to modeling the real data. From discussions in Section 5, we can conclude that the phone measurement models for GPS coordinates, speed, acceleration and number of nearby BT devices are useful in this modeling framework. The developed models will be implemented in the software package. A path generation algorithm will also be adapted for the generation of the set of potential true path.

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