# MobileSense - Sensing Modes of Transportation in Studies of the Built Environment

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#### Abstract

We discuss a study we conducted using the Mobile Sensing Platform and GPS information to record the activities and locations of 53 subjects, each of whom collected data for one week. Using this data we are developing methods for combining activity inference from sensors to infer the mode of transportation, label significant locations, and extract trips. Although our data collection was conducted using a non-consumer sensor platform, we discuss how our methods can translate onto existing mobile platforms such as the iPhone and Nokia N95, and how these platforms will enable us to study larger populations to draw more concrete conclusions about the relationship between the urban environment and people's activities.

# I. INTRODUCTION

As sensing platforms have advanced to become more usable and more readily available, the range of potential users and applications continues to expand. At the same time, commoditization of sensors in mobile phones has increased their availability and provided researchers with opportunities to study much larger populations than in the past. One area of interest in these sensors has been activity inference: the ability to tell what activities a person is performing based upon sensor information. Activity inference provides the 'what' of a user's context while location sensors (such as cell-tower/WIFI localization and/or GPS) provide the 'where'.

This 'what' and 'where' information can be used by a number of mobile phone applications, from physical fitness and health monitoring, to recommendation systems, to studying environment and personal behavior. In this paper we focus on the last application area, though the techniques we develop are applicable to a number of different applications. We worked with colleagues in the College of Architecture and Urban Planning's program on the Built Environment who are interested in studying the effect the urban environment has on the types of activities people engage in. Some of the questions these researchers are interested in are: what associations exist between different types of activities and different kinds of urban environments; what characterizes the land use patterns where people spend long periods of time; and do the properties of origins and destinations differ between short and long trips or trips made by different modes of transportation. To help answer some of these questions, we conducted a study to validate that sensors can be a useful tool for studies of the built environment, and to develop methods for performing these analyses on a larger scale. We collected one week's worth of sensor and GPS data from 53 participants. In all we gathered approximately 2,900 hours of data and ~2,900 surveys via the Experience Sampling Method (ESM) to provide ground truth. In the rest of this paper, we discuss the data collection, the methods we are developing to analyze the data, our validation for our method's usefulness, and our future work of implementing these methods on mobile phones to expand these studies to hundreds of users.

#### II. RELATED WORK

Mobile device-centric sensing has become an active area of research in the past few years. Several projects in the



Fig. 1. (left) Data collected from each subject with the amount of time a GPS lock was available. (right) Each line indicates a trace of data collected from subjects showing good coverage throughout the day and days of the week.

academic research community and the industry are quite relevant to this work. Agapie et al. [5] present the Personal Environmental Impact Report (PEIR) system in which they leveraged mobile devices to collect time stamped location data and use this information to build models that estimate individuals' impact on environmental pollution levels. Miluzzo et al. discuss the CenceMe system in [6]. CenceMe leverages sensing capabilities of Mobile Devices to infer contextual information such as activity, availability, surroundings, etc., and injects this "Sensing Presence" into social networking applications like Facebook and MySpace. Liao et al. [8] used GPS data alone with a relational Markov network to infer the activities a person performs based upon the time of day, GPS trace, and their proximity to stores and restaurants.

The Smartraq study investigated the relationship between objectively measured physical activity and objectively measured urban form; however, this relationship was based solely on subjects' home neighbrohood environment, rather than the complete spatial area of activity [7]. Mohan et al. discuss TrafficSense in [9], a framework in which they use sensors on mobile Smartphones to monitor road and traffic conditions, including mode of transportation.

#### **III. DATA COLLECTION**

For our data collection we wanted to collect GPS readings, accelerometer traces, and barometric pressure readings (which aid in detecting when people are moving up or down). Even though there are a few mobile phones such as the Nokia N95, and the new iPhone 3G, which have GPS receivers and accelerometers, these platforms are not yet perfectly suited to perform data collection necessary for our applications. While mobile phones excel in being robust, widely available, and relatively inexpensive devices; they often have restrictive security models, limited hardware access, poor documentation, and short battery lives. For example, the GPS receivers of the N95 and iPhone 3G are functional, but they do not provide data of an adequate quality for an initial experiment. These restrictions make it difficult to build data collection applications that need to run in the background for prolonged periods of time, a basic requirement for data collection in a research setting.

Instead we used the Mobile Sensing Platform (MSP) [3] which combines an Intel XScale processor with an accelerometer, barometric pressure sensor, light sensors, humidity sensors, microphone (not used in this experiment), GPS, and storage capacity. Subjects participating in the experiment were given an MSP inside a box with a belt clip, shown in Fig. 2, to be worn on their waist, and a cell phone for entering ground truth survey information.

Subjects were recruited to wear the device for a one-week period. During the week they would wear the MSP clipped on their waist and carry a Windows Mobile SMT phone wherever comfortable. The Smartphone was running the MyExperience ESM [2] sampling software, which would prompt them for a survey approximately every hour. These surveys asked questions about activity type, duration, purpose, and location (Fig. 2, middle). There were 53 participants with an average age of 32 and standard deviation of 11 years. Thirty-eight percent were female, and 86% were college graduates or had a post-graduate degree. On average each subject collected approximately 53 hours of data during a week. As subjects were allowed to turn off the device when they did not wish to be monitored, the amount of data collected varied among different subjects. Fig. 1 (left) shows a bar chart



Fig. 2. (left) GIS Data showing street roads, bus routes, and bus stops; (middle-left) Questionnaires that prompted users to enter survey data about the activities they were doing; (middle-right) Picture of mobile phone users carried to enter surveys; (right) sensor platform (MSP) shown out of the box and inside the box

indicating the total number of hours of data collected from each subject in blue, along with the lengths of time when a GPS lock was available shown in purple. The percentage of time when a GPS lock was available is shown for each subject as well; on average a GPS lock was available 66% (std. dev. 28%) of the time. Also shown in Fig. 1 (right) is a trace showing the start and end time of a recording session as a horizontal line, for all the data collected, organized by day of the week. The data collected is spread fairly well across the days of the week as well as covering most of the hours of the day.

#### IV. DATA ANALYSIS

The data collected from our experiment serves as a test bed for the development of our analysis methods and models. Of particular importance to this research is the fusion of Geographical Information System (GIS) data sources with GPS readings. While typically one might assume that GIS data are difficult to obtain and use; in reality, these datasets generally exist for larger metropolitan areas and are frequently freely available from local governments. Because of the added value of geographic information, rather than focusing our efforts on extracting information from the raw GPS and sensor trace without any prior knowledge, we use the GIS data layers to provide the location of features such as roads, bus routes and bus stops, building outlines, and land use to bootstrap our inferences. While the analysis methods presented here used data from our MSP sensing device, we are also investigating how well these methods and the associated infrastructure transfer to mobile phone platforms for the evaluation of similar methods with a variety of data sources and usage scenarios.

#### A. Mode of Transportation

One inference we want to make is to predict transportation mode for personal trips. Given the sensor information and GPS traces, we would like to determine when someone is in a car, a bus, walking, or riding a bike. Walking and bicycling activities tend to involve periodic movements (pedaling and stepping) that we can identify using a step detector based on accelerometer readings. Pedaling on a bicycle is somewhat similar to walking, but often exhibits distinct accelerometer and velocity patterns. When GPS information is available, we can make use of GPS velocity estimates to help differentiate between walking and cycling. Bicycling tends to have interspersed periods of pedaling and coasting, so within a series of GPS+sensor records, if we detect periods of rapid motion with no stepping, the series is more likely cycling than walking.

For cars and buses we can similarly use some sensor information because car/bus rides look very different from walking, i.e. the lack of steps. However, because of similar velocity and accelerometer patterns, differentiating between bus and car trips can be difficult. In this case the GIS methods become very useful; we can overlay a GPS trace on a general street grid as well as a bus route layer, as shown in Fig. 2. The blue trace shows a route which diverges predefined bus routes, which results in a higher confidence that the trip was made by car. Likewise, the red trace shows a trip of sufficient duration following a bus route, which also includes stops at mapped bus stop



Fig. 3. GPS trace showing the path a person followed over several days. Stationary GPS points are shown in red, moving points are shown in green. Inserts show the GIS layer information for several points along the person's path

locations, so this trip was more likely to have been made by bus. However, because of the staccato motion of stopand-go traffic, a car trip can also inadvertently appear to be a trip made by bus. Nevertheless, it may be possible to differentiate between car and bus trips based on the location of bus stops (versus random traffic stops).

# B. Extracting Trips and Dwell Locations

A majority of people spend their time at several distinct locations throughout the day: home, work, retail and grocery stores, restaurants, etc. From the data we have collected, we are particularly interested in identifying locations where people spend a great deal of time, and associating these locations with information about the built environment obtained from GIS data sources. Fig. 3, shows a GPS trace from several days of one of our subjects. In this figure we've colored the trace with points where the person was stationary and moving, along with several locations where they dwelled for long periods of time. The combination of activity information, GPS location, and GIS data provides a very rich information base for the investigation of spatial patterns of personal behavior. For practitioners of urban design, transportation planning, and public health, knowledge of how people in a given area interact with the surrounding environment would be invaluable. Do people living or working in a particular area have more or less physical activity? Do they tend to go out for lunch? What restaurants do they visit, what grocery stores do they purchase from, and how frequently? Do they walk, bike, drive, or take public transportation to get to nearby restaurants and stores? Do these patterns of behavior vary with the socioeconomic status of individuals or neighborhoods?

## C. Validation and Usefulness

In addition to the sensing and location information we collected from our subjects, we also asked them to answer hourly surveys asking questions about the type, duration, and location of activities they were performing. The purpose of these surveys was to provide some ground truth for evaluating the performance of activity inference. Ideally we would like to obtain fully labeled datasets; however, this is not feasible given the scale of data collection involved and, of course, cost limitations.

The surveys are used as testing data to verify that the automatically classified activity matches self-reported activity. However, unlike many statistical techniques, the ground truth here should be treated with some care; subjects may make mistakes in recording their activity or in estimating the true duration of continuous activity. For example, a subject walking home may have reported walking for 20 minutes but there may have been several minutes of window shopping, standing at crosswalks, etc. Due to these complications we have to be a bit more careful about how we incorporate the self-reported survey data for judging the accuracy of our methods. We are currently examining several methods and heuristics to determine which methods provide the best insight.

The question of usefulness for the GIS researchers is currently on an on-going research problem. As we complete more of the analysis of the data it will be possible to tease out more information from the data and determine if the

researchers' hypotheses are borne out by the experimental data. While the data set is quite large, in order to make conclusions that would affect urban design or public health policy for long term effects, it will be necessary to isolate fewer variables and conduct more longitudinal studies.

### V. CONCLUSION AND FUTURE WORK

While there have been several sensing platforms that have reached a large audience of researchers [4], [3]; in general large scale deployments have been the exception rather than the rule. However, with the commoditization of sensors in mobile phones, the audience of available end users is much larger than would be possible for traditional research platforms to reach. While mobile phones do have some limitations, their wide adoption and ever growing capabilities make them ideal for the next generation of location-based sensing applications.

The current methods we are developing are based on data obtained from the MSP and continuous GPS (when available). However, we are also conducting several pilot studies using the Nokia N95 and iPhone. The accelerometer data retrieved from the N95 and iPhone are quite similar to the data obtained from the MSP. A few important differences are that while the MSP is be clipped on the belt and not usually moved, the N95/iPhone would often be manipulated to look up information or to make calls, which would introduce noise that would need to be taken into account in our inference models. Another important difference is that the location stack on the iPhone provides several levels of localization: large scale cell tower localization, medium scale WiFi localization, and high-precision GPS localization. Rather than require the iPhone to continuously gather precise GPS readings, we are instead trying to use more coarse grain location estimates in our algorithms to more intelligently decide when to switch to more accurate (and power hungry) localizations. If a person is sitting at work inside a large building it makes little sense to try to get a GPS lock, instead we might be satisfied with the cell tower localization and only decide to obtain WiFi or GPS localization if we believe the person is leaving the building.

The study described in this paper has provided a large amount of useful data which we will be able to use in the design of algorithms and applications for mobile phones. However, while we were able to collect a great deal of data in this study, in order to be able to answer questions of how the urban environment affects what people do, we need to collect data for longer time scales and from more individuals. With the increasing capabilities and adoption of mobile phones, developing methods that can be implemented on mobile phone platforms opens up the possibility of reaching large audiences. But, at the same time, custom devices that are readily available are still important and both can provide useful data that is applicable to both custom sensing platforms and commodity mobile phones.

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