Toward Automated Detection of Risky Driving Behavior Patterns in Urban Environments

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Abstract. In Mexico, like in other countries, car accidents are the leading cause of death among young people. Therefore, the identification of drivers that can be potentially involved in car accidents is of particular interest. There are certain risky driving behaviors that are highly correlated to car accidents, including speeding, overtaking, and tailgating. In this work, we present a system for automated detection of risky driving behavior patterns in urban environments. The system makes use of GPS data to compute mobility traces and other several features useful to characterize driving behaviors. This work presents encouraging results toward automated identification of risky driving behaviors. Results from this work can be of interest for insurance companies, parents, police, and even for drivers' self-awareness of such driving behaviors.

1 Introduction

With the ever growing penetration of mobiles phones in people's daily activities and the emergence of increasingly cheap hardware components for tracking people and vehicles, there is a shift toward developing systems that can reach out of the desktop, even outside the home and work settings, in the city. These spaces between these two private locations have been referred to as third spaces [1] and have posed new opportunities for research in urban computing. Particularly, one of such opportunities has been receiving considerable attention from media and researchers: the development of systems for real-time tracking of persons and vehicles in large cities.

Of particular attention is the study of motor vehicles mobility as this is a major aspect associated with traffic accidents. In Mexico, car accidents are the leading cause of death among people under 30. According to the National Institute of Statistics and Geography (INEGI), in 2011 there were 387,185 car accidents in Mexico, from which around 95% were ascribed to human factors (e.g., distracted driving, drowsy driving, drunk driving). Also, in 2011 there were slightly more car accidents at 8, 14, 15, and 18hrs, which reflects that during the rush hour, the probability of being involved in a car accident increases, which is not surprising as such. Even more, age seems to be a factor, being young drivers those who experience more car accidents.

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The collection and study of mobility traces of motor vehicles can help identify risky driving behavior patterns of people. Researchers have analyzed these types of patterns in order to find appropriate strategies for reducing traffic accidents [2, 3]. In general, these studies have been conducted using questionnaires to ask people if they behave in certain ways and thus detect risky driving habits. However, as the authors of such studies state, this methodology may lead to inconsistences because of imprecise data provided by users [2]. In this sense, mobile technology provides an appropriate framework for the development of computational systems capable of collecting data regarding mobility traces of motor vehicles useful to identify risky driving behavior patterns. This technology based approach addresses the limitations of studies that make use of questionnaires as drivers' behavior is analyzed based on data collected in their daily life and, if desired, without awareness of the driver.

In this paper, we present a system based on mobile technology for collecting mobility traces of vehicles in urban settings. This collection of traces aims at detecting risky driving behavior patterns such as speeding and tailgating. This paper is organized as follows. In the next section we review related work. Then, in Section 3 we discuss basic requirements for identifying risky behavior patterns from mobility data collected using mobile technology. Afterwards, we present the design of the proposed system. Finally, preliminary results and closing remarks are provided.

2 Vehicle Tracking and Mobility Patterns

Many applications have been devised in the domain of urban computing. However, many of them need to carry out vehicle mobility tracking if they are to implement systems that use vehicles' location as input. For example, systems that use location for real-time tracking of fleet aimed at reducing costs in good manufacturing. In the literature, many of these types of systems use 'off-the-shelf' location systems (e.g., GPS units) whereas others manufacture in-house devices or applications for mobile phones. In particular, most research in vehicle tracking has been devoted to mainly study fleet management, understanding urban mobility, and enhancing road safety.

Fleet management involves real-time location of motor vehicles [4]. Fleet management systems aim at diminishing misuse of fleet, reduction of costs, and increase in safety of goods and drivers by knowing the whereabouts of their fleet (and drivers). In many cases, fleet management systems involve installing an in-car sensing unit that allows monitoring aspects that are of interest to the company such as fuel consumption, speed, and estimated time of arrival.

The second application is data analysis from mobility traces that can be used for urban planning. For instance, in [5] they collected data from GPS units installed in 30,000 taxicabs. The data were collected for two years and the analysis provided valuable insights for urban planners in terms of the zones of the city where most movement generated, which gave place to a redesign of traffic routes in the city. In a similar fashion, in [6] they used trajectories commonly followed by taxi drivers to create alternatives routes that could guide drivers through the fastest route, based on taxi drivers' experiences.

Lastly, for road safety there have been some systems created with the aim of reducing risks while driving. For example, CarSafe is an app that uses the front and rear cameras of a smartphone to provide alerts of risky driving behaviors such as drowsy driving or tailgating [7]. This behavior is not uncommon, as there are many people who drive while they are tired or drowsy [8]. DriveDiagnostics [9] is an in-vehicle data recorder used to monitor and analyze driver behavior. This system capture mobility traces that help determine overall trip safety and risky driving behavior by identifying and classifying a series of maneuver types.

In contrast to related work, the system proposed in this paper aims at taking advantage of the data collected only from GPS-enabled devices to detect patterns of risky driving behavior. These patterns are an essential requirement to classify users in terms of driving habits and to develop strategies for reducing traffic accidents.

3 Requirements for a System to Detect Risky Driving Behavior

There are several patterns of driving behavior that can be considered risky and that can be associated with traffic accidents. Detecting and analyzing such behavior patterns becomes important mainly for road safety purposes. Among other things, the causes of such behavior can be related to factors such driver's personality, using old vehicles, dangerous roads, or heavy traffic. This kind of information about driving behaviors and their potential causes are of interest to researchers, especially for the development of strategies for preventing traffic accidents.

Table 1. Behaviors or practices that can be identified using GPS information

Behavior	Identified?	Identification method
Aggressive driving	Yes	Speed data can be obtained from GPS data. Acceleration data can be computed
Breaking speed limits	Yes	Using geo-fences or marks on maps
Going through a Stop sign	Yes	Placing points of interest at stop signs (i.e., geolocation) and determining a speed threshold at that particular spot.
Going through red lights	No	Placing points of interest for traffic lights and determining the rate of stops made at this point
Changing lines	No	Identifying zones with multiple lines and detecting if drivers usually moves from one line to another
Overtaking	No	Computing speed and location difference, relative to other vehicles
Tailgating	No	Real time location and speed information of other vehicles is needed

As we mentioned above, data collected from GPS devices allow the monitoring and analysis of risky driving behavior. Commercial GPS devices generally provide a pair of geographic coordinates as well as visual information about current locations.

Most GPS-enabled smartphones can also provide these types of data. Moreover, through the Application Programming Interface (API) provided by the operating system of mobile devices, traces of GPS data along with speed, error, number of satellites used, and satellite timestamp can be usually obtained. Some aspects of risky driving behavior can be analyzed on the basis of such data collected from GPS-enabled smartphones. Nevertheless, there are limitations in terms of which patterns of risky driving behavior can be identified. Table 1 presents some examples of risky driving behavior and indicates which of them can be determined by using GPS data and which of them are addressed in this paper. Moreover, this table describes a possible pattern identification method.

4 Mobility Data and Risky Driving Behavior System Design

Given the requirements for risky behavior identification highlighted in section 3, we devised a system that could be scalable and flexible. Figure 1 illustrates the architecture of the system. There are three main elements: Mobile device (data collector), Server (data storage, retrieval, and analysis), and Web Client (data visualization).

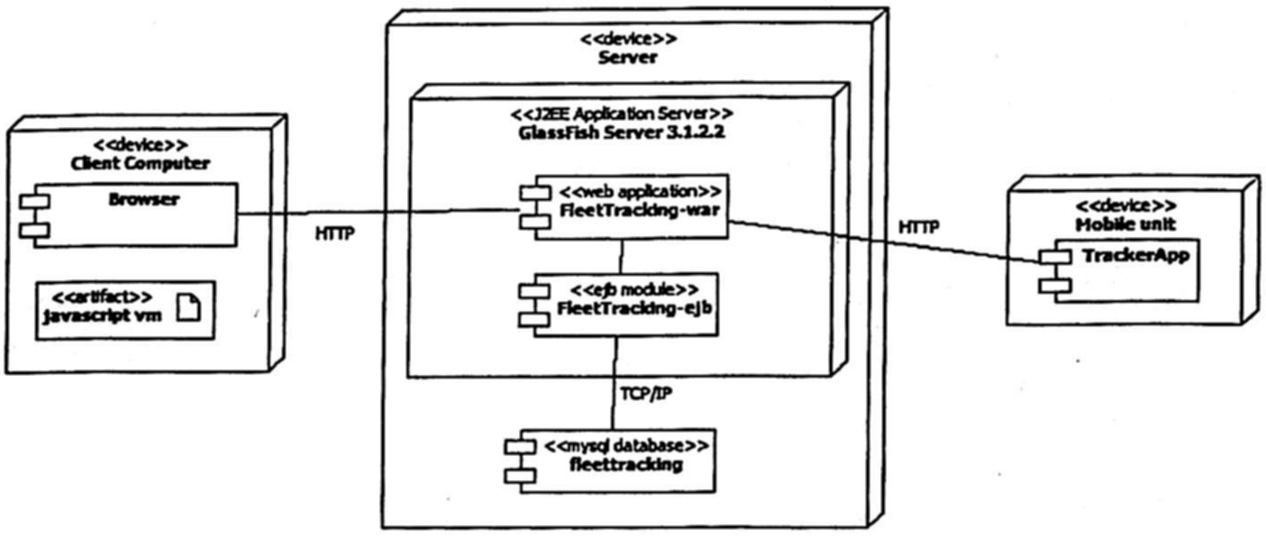

Fig. 1. Diagram showing the main components on the server and mobile device

- Web client: It is represented by the web client nodes, using a browser with JavaScript VM enabled. It comprises of two components:
  - Browser: It handles the communication between the web client and the web server.
  - Javascript VM: It is responsible for processing the information obtained from the server and showing it in a visual way.
- Server: The server node stores and processes the data collected and sent by mobile devices using HTTP GET commands. The system is deployed into an Application server which is composed internally by a web Server and a business server. It mainly comprises three components:

   - Web application (FleetTraking-war component): It works as the end point communications to mobile devices to send the data collected. Also, it works as the main application to which web client must connect to get traffic data. This element only contains presentation layer facilities.
   - EJB Module (FleetTraking-ejb): It is the main business logic module. All business logic is outside the presentation layer as a means to enable scaling using distributed processing.
   - Database: It stores and retrieves data. We used a MySQL 5.6 database.
- Mobile device: A mobile node where GPS data are collected. The mobile device can be any type of device that can make HTTP requests.
   - TrackerApp: We used a smartphone running Windows Phone 7.8, but the system is designed to allow any type of clients (e.g., smartphones of any make, devices with embedded software such as Arduino or Rasberry PI).

4.1 Main features of the System

The design of the architecture enables three main characteristics of the system:

- Scalable: It is based in distributed processing, one of the features of the Glassfish Java Application Server that conforms with the J2EE (java Enterprise specification), where business components can be distributed in several ways into Applications Servers Federations to raise up the process power of an application.
- Heterogeneous software environments: Communication between server and mobile devices is made through HTTP requests through a JSON (Javascript Object Notation) file.
- Flexible: As a main concern of the architectural design because of the heterogeneous nature of the environments where the applications are expected to work, we used the factory and strategy patterns, and the reflection mechanism to enable application adaptability to such changes. Also, using J2EE AppServer allow us to exploit intrinsic features related to change order process executions, pre and post conditions and message driven triggered business process among others, in many cases just by modifying XML configuration files.

5 Overview of the Deployment Area

Our experimental testbed was deployed in public transport in two cities in northwest Mexico (population around 120k and 400k). The cities' geography is mainly flat with a few buildings taller than 3 floors. The server was implemented on a laptop (Windows 8) with a Glassfish Java Application Server running. Communication with mobile devices was carried out via commercial mobile carriers (i.e., 3G). In addition, the Web client was implemented using standard technologies for web development (e.g., HTML5, CSS3, Javascript) and the Google Maps API.

5.1 Data collection

To facilitate the collection of samples, we designed a mobile phone-based application. The mobile phone used was a Nokia Lumia 710 running the Windows Phone 7.8. The application was collecting samples every 5 meters, meaning that the phone API provided an event whenever it detected a 5m change in location.

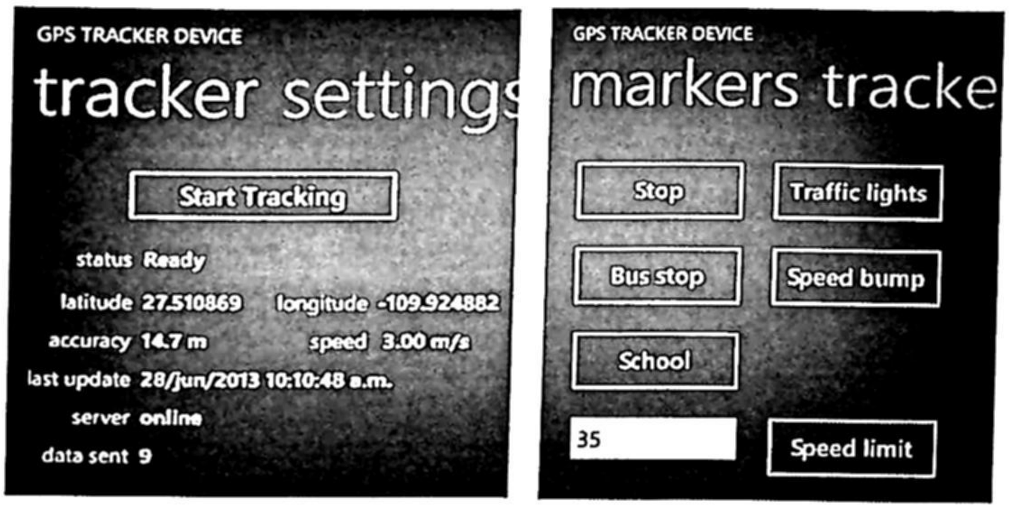

Fig. 2. Screenshot of the mobile phone app used for data collection

For this experiment, we collected samples 12,477 samples corresponding to three local routes of public transport in the aforementioned cities. Rather than extensive, the experiment was intended to test the functionalities of the system as well as the feasibility of detecting risky behaviors. We devised a heuristic to determine when a driver was externalizing risky behaviors. The analysis of the data was carried out offline using commercial spreadsheet software.

6 Results

This section presents preliminary results toward an automated detection of risky driving behaviors. In general, the analysis focused on detecting three main risky behaviors in drivers: aggressive driving, breaking speed limits, and going through a stop sign.

6.1 Aggressive driving

Aggressive driving is when a bus driver accelerates the vehicle too rapidly. Avoiding aggressive driving behavior can save around 25 liters of diesel per day [10]. According to [10], fuel consumption upsurges 67% for acceleration increase in the range of 0.5 m/s^2 to 1.5 m/s^2. This is highly relevant since the max acceleration detected in our experiment was 1.66 m/s^2. This is important not only for fuel optimization but also for passenger safety. In our experiment, the Min acceleration detected was -2.76 m/s^2, meaning that at some points of the route segment the bus driver braked sharply.

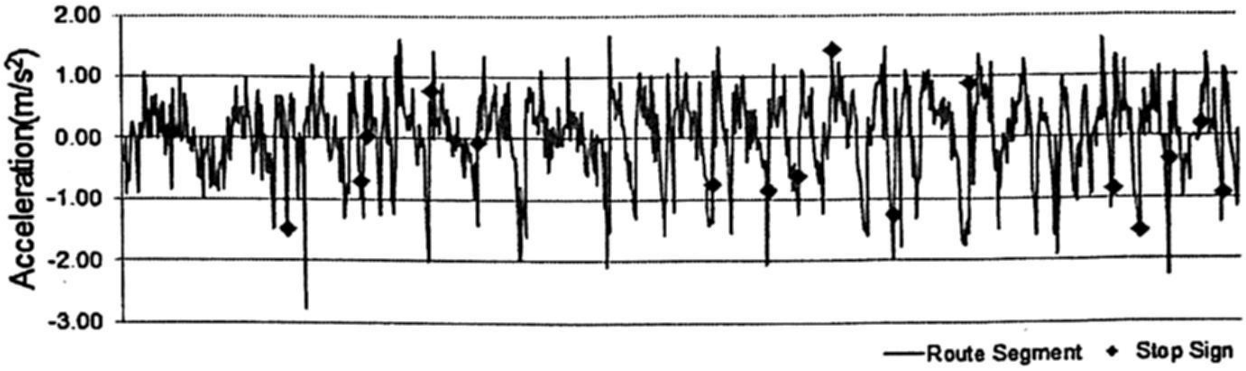

Fig. 3. Vehicle acceleration during a 30min window

Following Figure 3, we can observe the acceleration/deceleration at stop signs. In general, for this route segment, the average acceleration was 0.5 m/s^2, which is reasonable since an average sport car takes around 6s to reach 0.100 km/h at around 4 m/s^2. In Figure 3, it can be seen that the driver decelerates before stop signs in 11 times. However, there are two times in particular when the acceleration rate is really high at stop signs. For deceleration, the average was -0.53 m/s^2.

6.2 Breaking speed limits

According to the World Health Organization (WHO), speed control is one the various interventions likely to reduce road casualties. This is one of the reasons why is important to identify such behavior. In figure 4, we can see two street signs: stops and speed limits.

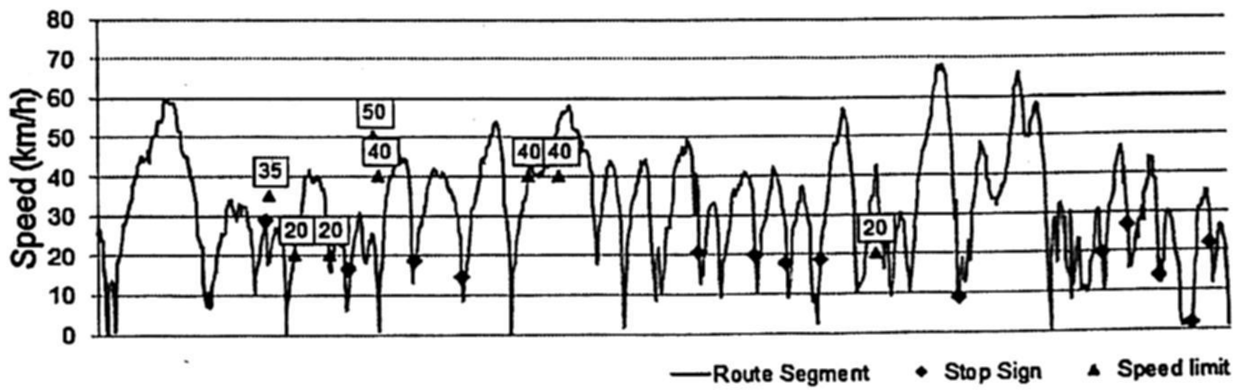

Fig. 4. Vehicle speed during a 30min window

Following Figure 4, it can be seen that speed is mainly decreased at stop signs. However, at only one stop sign the driver seemed to have made a full stop (speed below 10 km/h). The average speed was 32 km/h, and the max speed for this route segment is 68km/h. In this particular road segment, the driver seems to break the speed limits in two occasions. Still, from these data, it is difficult to determine when a traffic sign (e.g., speed limit at a school) is no longer relevant for the driver i.e., if the driver turns around a corner.

6.3 Going through a stop sign

In Figure 4, 16 stop signs are illustrated. However, it was difficult to detect if the driver made a full stop, as required by law. Instead, the driver seemed to have made semi-stops by reducing the overall speed of the vehicle. Two possible explanations arise. One the one hand, the driver does not stop at most stop signs, which can be worrisome as passenger and road safety must be paramount. On the other hand, this can also be caused by faulty GPS readings or error. Thus, additional experiments must be carried out to fully determine when a vehicle makes a full stop.

7 Closing Remarks

In this work, we presented preliminary results toward automated detection of risky driving behaviors. We carried out an experiment to determine the feasibility of detecting such behaviors with GPS data. Future work includes combining the results from analyzing risky driving behavior with other kind of information such as drivers' background and driver affective condition when exhibiting risky driving behavior as well as with information about city zones and places of interest. This may help to understand the relation of people's background and their driving habits. Thus, this can lead to strategies for improving people driving behavior and increasing road safety.

8 References

1. Shklovski, I. and M.F. Chang, *Urban Computing: Navigating Space and Context*. Computer, 2006. **39**(9): p. 36-37.
2. Ivers, R., et al., *Novice Drivers' Risky Driving Behavior, Risk Perception, and Crash Risk: Findings From the DRIVE Study*. American Journal of Public Health, 2009. 99(9): p. 1638-1644.
3. Blows, S., et al., *Risky driving habits and motor vehicle driver injury*. Accident Analysis and Prevention, 2005. **37**(4): p. 619-624.
4. Ghoshal, S., *Automatic Fleet Management System*, 2008, Jadavpur University. p. 86.
5. Zheng, Y., et al., *Urban Computing with Taxicabs*, in *13th ACM International Conference on Ubiquitous Computing (UbiComp 2011)*2011, ACM Peess: Beijing, China.
6. Yuan, J., et al., *T-drive: driving directions based on taxi trajectories*, in *Proc. of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems (GIS 2010)*2010, ACM: San Jose, California. p. 99-108.
7. You, C.-W., et al., *CarSafe App: Alerting Drowsy and Distracted Drivers using Dual Cameras on Smartphones*, in *11th International Conference on Mobile Systems, Applications and Services (MobiSys 2013)*2013, ACM: Taipei, Taiwan.
8. Sahayadhas, A., K. Sundaraj, and M. Murugappan, *Detecting Driver Drowsiness Based on Sensors: A Review*. Sensors, 2012. 12: p. 16937-16953.
9. Toledo, T. and T. Lotan, *In-Vehicle Data Recorder for Evaluation of Driving Behavior and Safety*. Transportation research record, 2006. 1953: p. 112-119.
10. Rohani, M.M., *Bus Driving Behaviour and Fuel Consumption*, in *School of Civil Engineering and the Environment*2012, University of Southampton: Southampton, UK.