AN IN-VEHICLE INFORMATION SYSTEM PROVIDING ACCIDENT HOTSPOT WARNINGS

Prototype

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Abstract

Accident hotspots, locations where accidents are historically concentrated, contribute significantly to road traffic accidents being the leading cause of death by injury. A notable improvement in driver safety can be achieved through warnings of known upcoming hazardous features. However, as installing and maintaining traditional road sign infrastructure can be costly, warnings on accident hotspots are not typically available. This paper presents an in-vehicle information system prototype which provides warnings of upcoming accident hotspots based initially on historic data. Additionally, significant research has focused on the identification, analysis and treatment of these accident hotspots. However, a true picture of road safety can be hard to achieve as many traffic accidents go unreported. Information on near-miss events, such as heavy braking or taking evasive action to avoid an accident, could help identify and provide life saving insights into hazardous areas before an accident occurs. The prototype therefore additionally collects vehicle data in order to learn characteristics of accident hotspots and identify near-miss events, in order to improve the system and provide new insights.

Keywords: In-Vehicle Information System, Accident Hotspot, Historic Accident Data, Vehicle Data

1 Problem Statement

Road traffic accidents are the leading cause of death by injury, as recognised by the *World Health Organization* (2013). Although there is a lack of a common definition among existing research, an accident hotspot can be identified as a location where road traffic accidents have historically been concentrated. There are many potential causes for such concentrations of traffic accidents, such as inadequate perception of the curve of a road, polished pavement and faded horizontal markings (Montella, 2010). Significant research has focused on the identification, analysis and treatment of these accident hotspots (Montella, 2010), typically using historic or simulated accident data (Persaud and Hauer, 1984; Cheng and Washington, 2005). However, a true picture of road safety can be hard to achieve as many traffic accidents go unreported (Agran and Dunkle, 1985). Additionally, frequent near-miss accidents, such as heavy braking or taking evasive action to avoid an accident, could help identify and give life saving insights into hazardous areas before an accident occurs.

Although advancements in areas such as autonomous braking (Fildes et al., 2015) hope to reduce the number of fatalities from traffic accidents, road sign infrastructure remains an important factor in conveying safety information to drivers. Persaud, Hauer, et al. (1997) demonstrated that significant improvement in driver safety can be achieved through warnings of upcoming hazardous road features, such as sharp corners and icy conditions (Carson and Mannering, 2001), thus mitigating the risk of vehicle accidents. However, according to the *International Road Federation* (2006), the cost of installing and maintaining this infrastructure can be high.

In order to combat these problems, the present research aims to develop an in-vehicle information system with the goal of improving driver behaviour and awareness through potentially dangerous locations. Non-intrusive information to the driver will be presented on upcoming hazardous areas in order to encourage safer driving through accident hotspots. In parallel to this, data from the vehicle will be collected to train the system to identify new potentially hazardous areas.

We present an in-vehicle information system prototype which provides warnings of upcoming accident hotspots based initially on historic data, and collects vehicle data in order to learn characteristics of accident hotspots to improve the system and provide new warnings. The remainder of this paper is structured as follows. The next section briefly reviews the state of the art of the various components of the system. This is followed by an outline of the design process and description of the information system. A section then describes the evaluation of the prototype and preliminary results are presented. Finally, a discussion of the contributions to theory and practise of the prototype, limitations and the intended next steps of the research concludes the paper.

2 State of the Art

2.1 Accident Hotspot Identification and Analysis

Identification and analysis of accident hotspots has been researched significantly (Montella, 2010), and typically utilises historic or simulated accident data (Cheng and Washington, 2005; Persaud and Hauer, 1984). This paper follows the assumption of Anderson (2009), that spatially dependent road accidents occur in similar areas. One approach to identify hotspots from historic data is to use clustering techniques to group together the events, and a review of these algorithms is provided by Jain, Murty, and Flynn (1999). K-means is a common clustering technique for identifying geospatial locations of statistical hotspots. Alternatively, Anderson (2009) argues that kernel density estimation (Sabel et al., 2005; Chainey and Ratcliffe, 2013) can help determine the spread of risk of an accident, thus providing an advantage over traditional methods. The author additionally uses the variance of variables of accidents which contribute to a hotspot as a basis to categorise and compare similar types of accident hotspots.

Once accident hotspots have been identified, it is necessary to be able to store the locations of these in order to be able to provide accurate warnings to drivers. Reliably predicting the future position and determining whether the trajectory of a vehicle will intersect with a cluster is non-trivial, and initial experiments found that clusters are difficult to use in a vehicle information system. As an example, it is challenging to display relevant warnings when a vehicle is approaching a detected accident hotspot via a bend in the road. However, these issues can potentially be overcome through incorporating knowledge of the layout of the road infrastructure.

Using existing knowledge of the road system to predict a location is known as map-matching, and an excellent overview to the topic is provided by Quddus, Ochieng, and Noland (2007). The authors outline a selection of map-matching techniques, which can be roughly grouped into four different types: Geometric, Topological, Probabilistic and Advanced. A selection of geometric map-matching techniques are outlined by Bernstein and Kornhauser (1998) and White, Bernstein, and Kornhauser (2000). The most commonly used is point-to-point matching, a simple search algorithm identifying the closest node or road segment from a given positional point, as it is the easiest to implement. A downside to point-to-point of-matching is that it is sensitive to the digital data used to represent or map the roads (White, Bernstein, and Kornhauser, 2000). This can lead to problems in practise, especially when combined with inaccurate positional data such as the Global Positioning Service (GPS). However, initial experiments showed that it is still considerably better to use the technique to determine if a vehicle is approaching a hotspot, than to rely solely on the vehicle trajectory. Topological map-matching techniques extend the Geometric approach, making use of the relationships in the digital representation of the road network. For example, representing a section of road as a line between two points, and matching to a position on the line to find a more accurate location. In order to counter the inaccuracy of GPS positional data, Probabilistic map-matching techniques typically introduce a confidence region around a position, this region is then incorporated when mapping to a road network. Finally, Advanced techniques make use of more computationally complex methods, such as Kalman or Extended Kalman Filters and Dead Reckoning.

2.2 Insights from Driving Data

Due to the wide availability of devices, recent research effort has identified the capability for smartphones to be used as a source of driving data. As well as GPS connectivity, modern smartphones are typically equipped with an inertial measurement unit (IMU) to provide three-dimensional acceleration values. Additional sensors such as a smartphone's camera and microphone can also be utilised for detection of various driving related activities. An example of this is seen in Mednis, Elsts, and Selavo (2012), who detect road roughness conditions and features, such as potholes and man-hole covers, using a mounted smartphone's accelerometer and microphone data. Studies have also introduced signal processing techniques that can provide an indication of driving events and behaviour using the accelerometer data provided by a smartphone. These include Johnson, Trivedi, et al. (2011), who used sensors in a smartphone to identify driving style, differentiating between aggressive and non-aggressive driving manoeuvres, and Paefgen et al. (2012), who detect various driving events using only a smartphone's IMU.

However, a limitation of these approaches is that the smartphone must typically be mounted in the vehicle to obtain accurate results. If the smartphone is moved while driving then false positives for events and road features will almost certainly be introduced into any system. One option to overcome this limitation, explored by Tin Leung et al. (2011), is to add an additional mounted IMU to a vehicle and use the same techniques. An alternative approach is to make use of data from the vehicle itself. On-board diagnostics (OBD) data is widely available in a standardised format for all vehicles built and sold in the Unites States after 1996, and so has been a focus in a variety of research projects. For example, Imkamon et al. (2008) extract the Vehicle Velocity and Engine Speed (RPM) to assist in detecting hazardous driving behaviour.

Yet OBD data is a small subset of the data that is potentially available within a vehicle. The Controller Area Network (CAN) Bus holds unstandardised information on the inner-workings and communications between subsystems of a vehicle. This data can potentially provide much deeper insights into causes of accident hotspots as well as road conditions and driving behaviour. CAN data has been utilised in several papers, Karaduman et al. (2013) used data found on the CAN Bus to identify characteristics of aggressive and calm driving behaviour. Additionally, Ferreira, Almeida, and Rodrigues da Silva (2015) and D'Agostino et al. (2015) make use of the CAN Bus of several vehicles to identify fuel efficient driving behaviour.

3 Prototype Description

The in-vehicle information system was developed through multiple build and evaluation stages, typical of iterative development, following the design science research paradigm (Hevner et al., 2004; Peffers et al., 2007; Gregor and Hevner, 2013). The prototype was developed in conjunction with regular drivers over the course of a year, comprising of surveys and an initial field test of eight drivers for approximately two weeks, where approximately 5,000km were driven.

Any information system providing warnings on upcoming accident hotspots will only be able to deliver value to users when information is known about the area the vehicle is currently traveling. The prototype system considers the vehicle itself as a sensor in order to detect accident related driving behaviour, such as hard braking or heavy swerving (Imkamon et al., 2008; Karaduman et al., 2013). As some road traffic accidents are unreported, vehicle data could also detect hotspots of 'near-accidents', where drivers frequently show accident related manoeuvres. The challenge with this approach is that it requires a certain amount of data before a hazardous area can be reliably reported. Therefore, if relying solely on vehicle data the prototype would initially offer a severely reduced warning service, giving drivers little incentive to use such a system. That is, the prototype faces a cold-start problem which is typical for services with network effects (Rochet and Tirole, 2003; Shy, 2011). The alternative method is to rely on historic data of accidents to initially identify hazardous areas (Persaud and Hauer, 1984). The presented prototype therefore uses historic accident data to tackle this cold-start problem, providing initial warnings to the driver on the basis of the historic data. Additionally, this historic data can then be used to validate the hazardous area detection from vehicle data. Through the combination of such data, potentially hazardous areas could be detected more efficiently and reliably.

The in-vehicle information system prototype is constructed from three components, and this section describes these and how they interact. First, a smartphone application is the medium to provide the approaching accident hotspot information to the driver, it additionally provides a variety of eco-driving feedback when not in a hazardous area. Second, the backend server architecture stores the locations of historic accident hotspots, calculates when a vehicle is in an area where a warning should be shown, and additionally processes the data collected from the vehicle to detect new possible hazardous areas. Finally, the driving data from the vehicle is collected through a Bluetooth OBD-II dongle, this data is passed to the smartphone in the vehicle and transmitted in real-time to the backend server for analysis. Figure 1 provides a high-level overview of the information flow of the system.

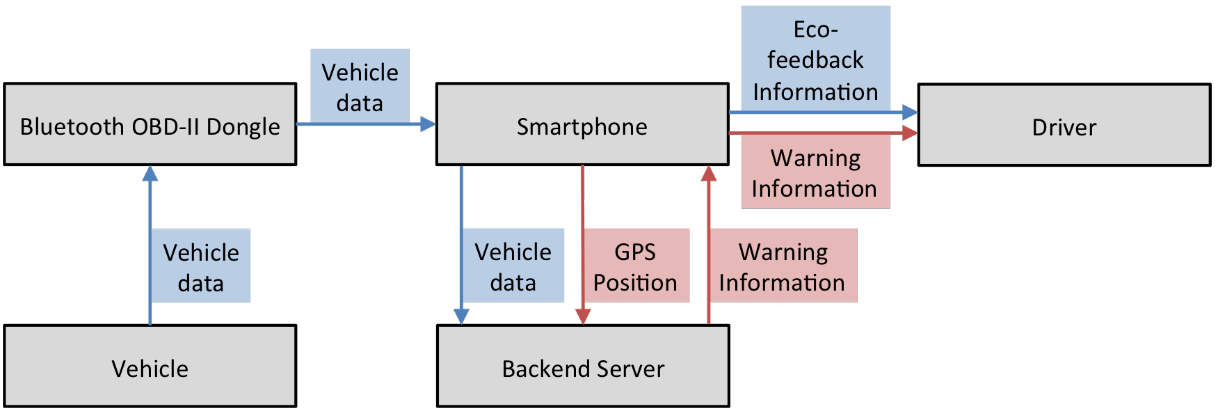

Figure 1. High-level overview of information flow of the system. Blue indicates vehicle data flow, red indicates accident hotspot information flow.

3.1 Smartphone Application

The Android smartphone application is separated into two sections, non-warning feedback and warning feedback. In order to encourage use of the information system, a variety of non-warning eco-driving feedback is provided to the user when not travelling through accident hotspots. There are two types of eco-driving feedback available for the driver to choose. The first is concrete feedback which extends the vehicles dashboard and provides realtime fuel consumption information. The second is abstract feedback, where a tree grows and shrinks based on the average fuel consumption of the current trip. Figure 2 shows these two types of eco-driving feedback.

Figure 2. Non-warning feedback provided by the information system. From left to right: concrete fuel efficiency, abstract fuel efficiency.

When the smartphone is informed by the backend server that the vehicle is approaching an accident hotspot, the eco-driving feedback is replaced by warning feedback. The warning feedback displayed varies based on contextual information available about the accident hotpot. When the accident hotspot is constructed from historic data, information is displayed showing the number of accidents and the predominant type of accident. As an example, an accident hotspot is categorised as 'rear-end collision' when the majority of accidents making up the hotspot are of this type. When the accident hotspot is constructed from vehicle data, the number and predominant type of incident is presented to the driver.

Klauer et al. (2006) demonstrated that, in general, brief glances away from the forward roadway, for the purpose of scanning the driving environment and the in-vehicle instrument cluster, are safe and decrease crash and near crash risk. This alertness is behaviour we aim to encourage through warning of a potentially hazardous area. The authors additionally found that a short glance from the forward roadway for a simple task only increases marginally, if at all, the risk of a crash or near crash while driving. However, the importance of non-intrusive interactions with the driver are also highlighted. The authors indicate that the risk of a crash or near crash increased twofold over normal driving behaviour when longer times of inattention were observed. In order to reduce driver inattention due to the accident hotspot warning functionality, and convey actionable information to the driver, audio and visual warnings were implemented as outlined by Cao et al. (2010). Figure 3 provide examples of both the historic accident and vehicle data hotspot information warnings.

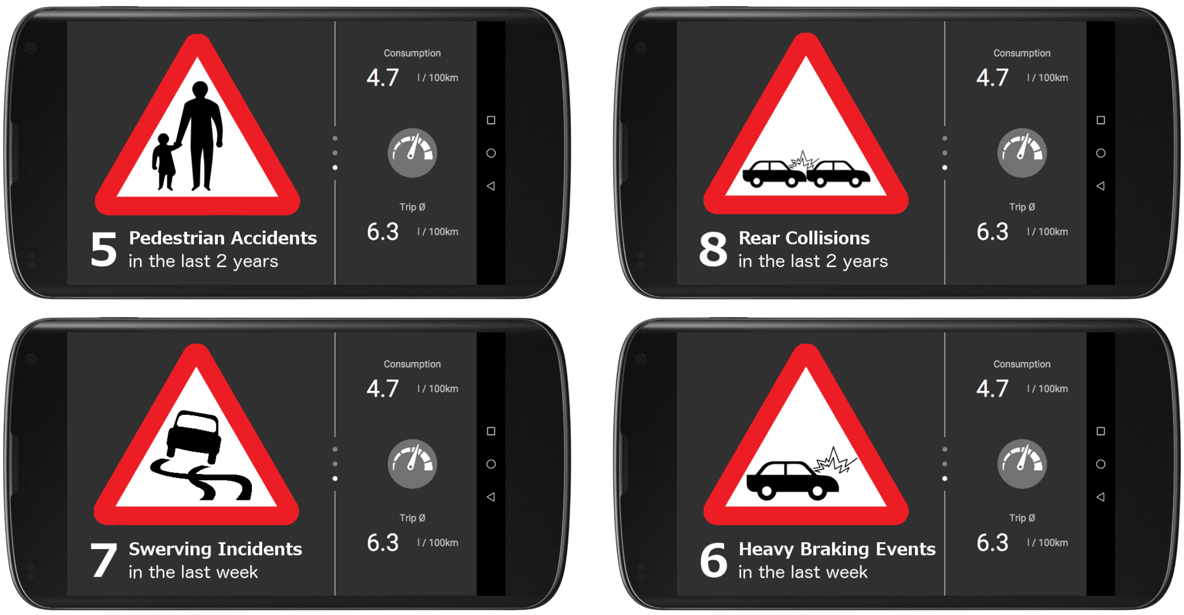

Figure 3. Examples of warning feedback provided by the information system. Top row: historic accident hotspot warnings. Bottom row: vehicle data hotspot warnings.

3.2 Backend Server

In the early stages of the system, when little vehicle data has been collected, the prototype is unable to provide vehicle data hotspot feedback to users. Therefore, historic accident data from 2011-2014, provided by the Swiss Federal Roads Office (FEDRO), is used to counter this cold-start problem and generate historic accident hotspot warnings. This data contains over 213,000 geo-located accident records across the entire Swiss road network, and includes detailed contextual information describing each accident. The initial accident hotspots are generated from this data using the kernel density estimation technique, as described in Section 2.

Initial experiments showed that a point-to-point map matching algorithm, with freely available *OpenStreetMap* (2015) data as the digital data input, was suitable for storing the locations of detected accident hotspots. OpenStreetMap provide digital map data in the following format, GPS points making up a road network are referred to as 'nodes' with a unique ID, and individual sections of roads, known as 'ways', are a collection of these nodes. Sections of road that intersect can be encoded using this approach through two or more ways sharing the same node. The implemented point-to-point map-matching technique finds the closest way to a provided GPS coordinate, and then returns the closest node on the identified way and associates the hotspot with this node's unique ID. This node ID is then the basis for providing warnings for specific sections of road.

The same point-to-point map matching technique as outlined above was additionally suitable for identifying a vehicle's current road segment in real-time, essential for providing relevant warnings to drivers. The smartphone application transmits the vehicle's location to the backend infrastructure whenever the GPS location changes. The backend process then finds the closest way to the GPS coordinate, and then returns any warnings associated with nodes which are encompassed in this way. These warnings are then displayed to the driver through the information system. A limitation of this approach is that it relies on the GSM connection of the smartphone to receive relevant warning for the current road being driven on.

Finally, the backend server utilises the latest Big Data (Manyika et al., 2011) technology in order to process the high volume and frequency of data being transmitted from each vehicle. Apache Kafka, Storm, Cassandra and Spark (Ranjan, 2014) are used to process the messages in realtime and identify potential hazardous areas from the vehicle data.

3.3 Vehicle Data

In order to retrieve and collect driving data from a vehicle's CAN Bus, a Bluetooth dongle is connected to the vehicle via the OBD-II port. When access to the CAN Bus of a vehicle is not restricted, then the messages transmitted from the vehicle's internal sensors can be obtained. The Bluetooth dongle is configured to interpret CAN messages on compatible vehicles, where access to the CAN Bus is available. These signals and messages are unstandardised and vary between makes and models of a vehicle.

The dongle is linked through Bluetooth to transmit CAN messages from the vehicle to the smartphone at a maximum rate of 30hz per measurement. The smartphone collects these CAN messages and, along with its own internal GPS data, streams these to the backend server via GSM in real-time. Based on the prior research into driving related insights, the following measurements were identified and are collected for the purpose of identifying hazardous areas:

- Engine Speed (RPM)
- Individual Wheel Speed (km/h)
- Vehicle Acceleration (m/s^2)
- Throttle Pedal Position (%)
- Brake Pedal Position (%)
- Steering Wheel Angle (deg)
- Longitudinal Acceleration (m/s^2)
- Lateral Acceleration (m/s^2)
- Yaw Rate (deg/s)
- Antilock Braking System (ABS) Activation

- Electronic Stability Program (ESP) Activation
- Traction Control System (TCS) Activation
- Wheel Slip Status
- Outside Temperature (°C)
- Windshield Wiper Activation
- Headlight Setting and Activation

4 Prototype Evaluation

The prototype will be evaluated through a longitudinal field study of professional drivers, travelling for approximately four hours a day in Switzerland. The study will be conducted with two groups, where drivers in both groups will receive the full prototype system. The smartphones in both groups will be initially limited to display only fuel efficiency related driving data. After an initial baselining phase: (a) the control group will have no change, and (b) the second group will have warnings enabled. When creating these groups, randomisation checks will be conducted over variables such as driver location, average trip length and time of day. Changes in driver behaviour through hazardous areas will be evaluated, using data collected from the vehicles such as speed, acceleration and braking behaviour. Additionally, surveys of the group members will be undertaken to track subjective measures, such as perceived usefulness of the warning system.

4.1 Preliminary Results

A preliminary field test was undertaken with a small fleet of eight vehicles, for approximately two weeks, in order to collect initial data and to test the system. The vehicles did not have the warning feature enabled and the information system only provided eco-driving feedback. A preliminary exploration of the CAN data collected from the vehicles indicates promising correlations to historic accident hotspots. An example is shown in Figure 4, where heavy longitudinal deceleration could be used to identify historic accident hotspots.

Figure 4. Preliminary results showing link between driving data and accident hotspots. Background image shows areas of heavy longitudinal deceleration in blue. Foreground image shows historic accidents in green and locations of accident hotspots with red markers.

5 Conclusion and Contribution

This paper presents an in-vehicle information system prototype that looks to solve two practical problems. First, as installing and maintaining traditional road sign infrastructure can be costly, warnings on accident hotspots are not typically available. Thus the prototype provides non-intrusive warnings on hazardous sections of road to drivers, in order to encourage awareness and safe driving behaviour through known accident hotspots. Second, as many traffic accidents go unreported it can be hard to achieve a true picture of road safety. Frequent near-miss accidents, such as heavy braking or taking evasive action, could help identify and give insights into hazardous areas. Therefore, vehicle data is collected by the system for analysis, in order to identify new possible hazardous areas and potentially provide life saving information before an accident occurs.

Longitudinal studies will be conducted with a fleet of professional drivers to evaluate the system. This could lead to further theoretical contributions, specifically on the impact of warnings provided through in-vehicle information systems to encourage safe driving behaviour. Furthermore, evidence-based knowledge on the effects of in-vehicle information systems on driving behaviour could be generated, and how these effects change over time. Additionally, alternative warning information can be presented, such as number of deaths or injuries linked with an accident hotspot, replacing the current contextual information displayed. This could contribute to future information system design, providing insights into the type of feedback which is most effective at modifying and encouraging safer behaviour.

A limitation of the prototype is that the smartphone is reliant on a stable and fast GSM connection in order to provide accurate warnings to the driver. Future efforts on developing to the system will investigate the accuracy of alternative techniques that can operate with limited connectivity. Examples of these techniques include geo-fencing or caching data required for map-matching on the device, however, this data would likely take up a significant amount of memory on the phone. This work would additionally overcome a second limitation, where constant communication to the backend server could quickly impact the smartphone's battery and GSM data usage.

In conclusion, the presented information system provides warnings of upcoming accident hotspots based initially on historic data. The prototype additionally collects vehicle data in order to learn characteristics of accident hotspots to improve the system and provide new warnings. With the rise of connected vehicles, the warning functionality could be incorporated into a vehicle's in-built entertainment or navigation system, or alternatively other internet enabled devices such as dedicated navigation accessories. This digitised warning system therefore could present benefits through helping to mitigate accident risk and augmenting existing road sign infrastructure.

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