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Driver Safety Improvements Using Data From Smartphone Sensors

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ABSTRACT

A safe and smooth driving experience is one devoid of stressful events. To improve overall trip smoothness and driver safety, with user permission, the techniques of this disclosure utilize environmental factors (e.g., road geometry, weather, narrow lanes, etc.) and identify risky driver actions (e.g., speeding, sharp deceleration, etc.) to predict the likelihood of an unfavorable driving outcome. With user permission, dangerous driving maneuvers are identified using data from smartphone sensors such as GPS and inertial sensors such as the accelerometer, gyroscope, and magnetometer, e.g., on a smartphone or other device in the vehicle. A machine learning model, provided as part of a smartphone application, such as a mapping and navigation application, is utilized to analyze the data obtained from the inertial sensors. Results from the machine learning model are used for mitigation strategies such as routing advisories, dynamic UI alerts, refinement of driver assistance features, etc., designed to reduce or eliminate unfavorable driving outcomes.

KEYWORDS

- Driver safety
- Road safety
- Inertial sensor (IMU)
- Dangerous maneuver
- Risky maneuver
- Automobile accident
- Collision
- Mapping and navigation

BACKGROUND

    A safe and smooth driving experience is one devoid of stressful events. Whether as mundane as dealing with stop-and-go traffic or as severe as needing to dramatically change the vehicle speed, stressful events create a friction that can weigh heavily on the minds of drivers and can put them at increased risk, e.g., of collisions or other dangerous events. It is known that unfavorable outcomes occur due to environmental factors (e.g., road geometry, road quality) in combination with driving actions (e.g., driving over the speed limit, sudden acceleration or deceleration, etc.)

    Vehicle collision data is commonly used to measure road safety. Several sources are available, some of which are public (e.g., from local municipalities or the federal government) while others are proprietary (e.g., insurance companies). Such collision data is limited in that it is sparse (since vehicle collisions are rare events) and incomplete (data is inconsistently reported and/or its use is restricted). Some techniques include detection of non-crash traffic "conflicts" for road safety analysis. However, such techniques use field observation, computer vision techniques, or naturalistic driving studies as data collection methods. These are onerous and expensive to deploy.

DESCRIPTION

    This disclosure describes techniques to automatically determine situations that can lead to unfavorable driving outcomes and proactively provide users with alerts to eliminate or reduce such outcomes. To that end, with user permission, data from sensors from a device (e.g., smartphone or other device) that is present on-board a vehicle are obtained and utilized to determine the likelihood of an unfavorable driving outcome. A trained machine learning model is

used to analyze the data and results from the model are utilized to take mitigating actions that can reduce or eliminate unfavorable driving outcomes.

Unfavorable driving outcomes can result from a combination of environmental factors and maneuvers executed by a driver. With user permission, such environmental factors as well as vehicle maneuvers are determined. To this end, data from inertial measurement unit (IMU) sensors and/or other sensors on a smartphone (or other device) on-board the vehicle can be obtained and analyzed with user permission
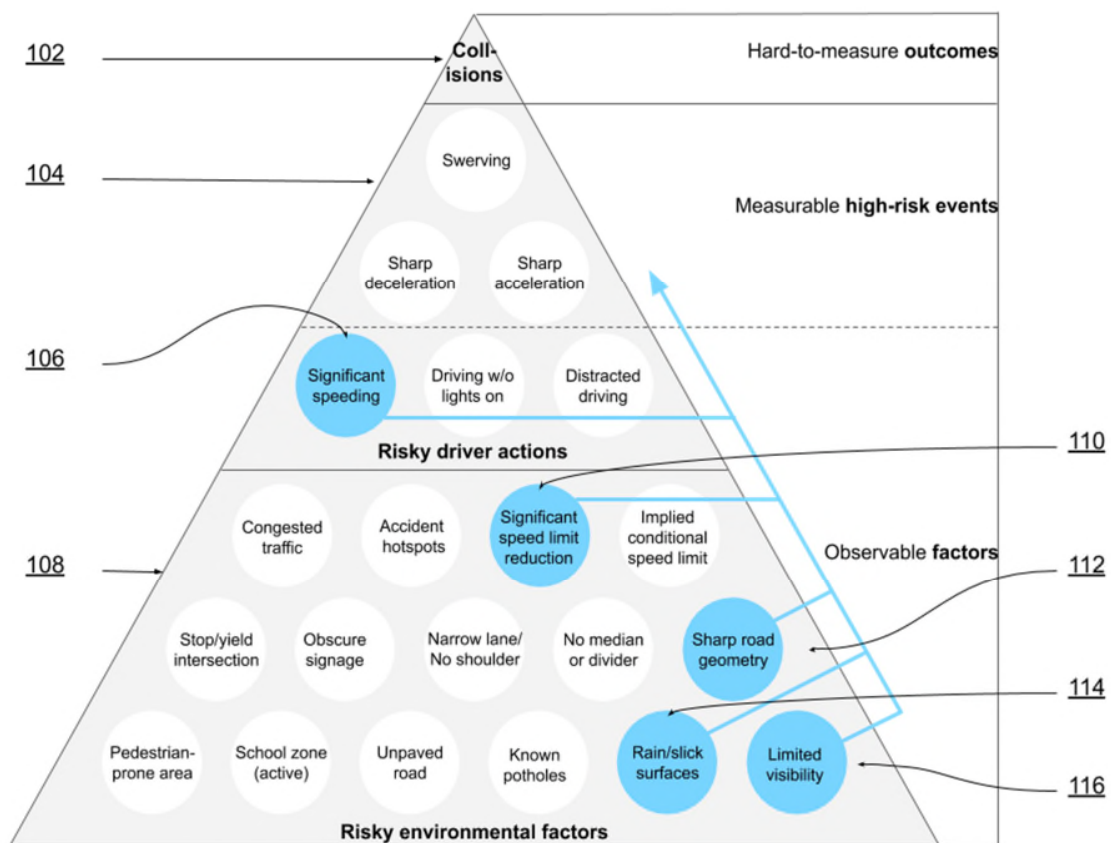

Fig. 1: Example of a risky driving scenario

Fig. 1 shows an example of circumstances that may lead to an unfavorable driving event. In the example illustrated in Fig. 1, a hard-to-measure undesirable outcome is a collision (102). High risk driving actions (104) include actions such as swerving, sharp deceleration or

acceleration, speeding, driving without lights on, distracted driving, etc. In the example shown in Fig. 1, one such factor is detected - significant speeding (106).

Risky environmental factors (108) that can contribute to such an outcome can include one or more of obscure signage, narrow lanes or lanes with no shoulder, potholes, limited visibility, sharp road geometry, no median or divider, etc. In the example shown in Fig. 1, four such factors are detected (shown in blue) - significant speed limit reduction (110), sharp road geometry (112), rain or slick surface (114), and limited visibility (116).

While specific prediction of when a collision may occur is difficult, it is possible to automatically identify circumstances that put a driver at a higher risk of accident. In the example scenario of Fig, 1, the user is driving a vehicle and is about to exit a highway on a rainy night. It is determined that the exit includes a sharp turn. Further, it is determined that the user is driving substantially over the speed limit. Thus, a risky driver action (106) as well as multiple environmental factors (110-116) are identified.

When such data is provided to a trained machine learning model, the model can generate a prediction, e.g., that the example scenario of Fig. 1 is associated with a high likelihood of an unfavorable driving outcome, e.g., a collision.
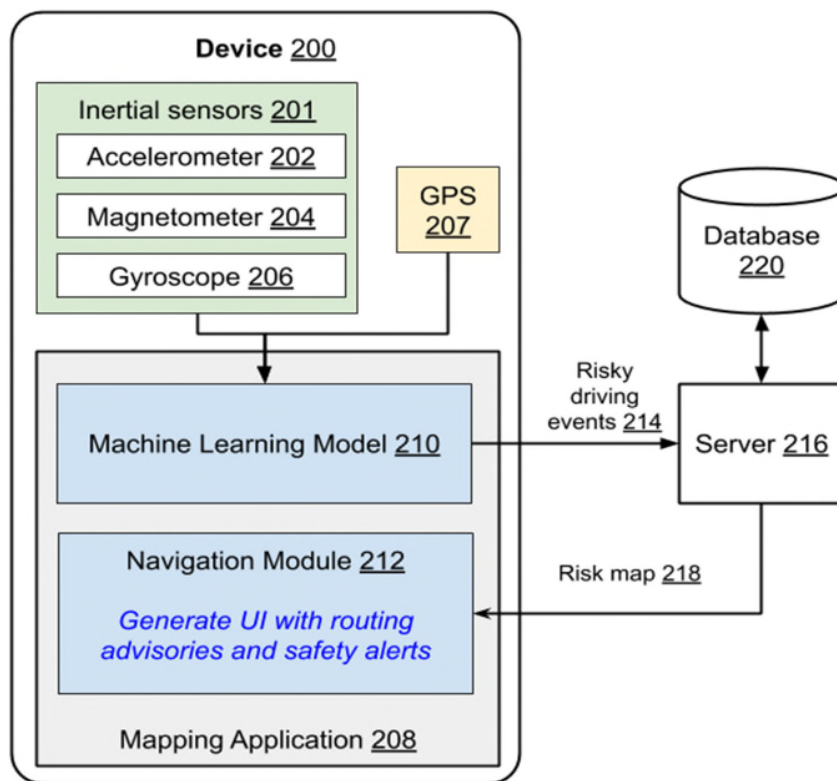
Fig. 2: Identifying risky driving scenarios and mitigating them

With user permission, data from inertial sensors, such as accelerometers, gyroscopes, and magnetometers in devices such as smartphones that are often present in moving vehicles is utilized to determine the various factors described above with reference to Fig. 1. As shown in Fig, 2, data from inertial sensors (201) that include, e.g., an accelerometer (202), magnetometer (204), and gyroscope (206), and a global positioning sensor (GPS 207) of a smartphone (200) are sent to a mapping application (208). A machine learning model (210) trained to predict the likelihood of undesirable driving outcomes is included in the mapping application.

Unsafe driving events, e.g., hard swerving, braking, acceleration, etc., are detected by the machine learning model. For example, such driving events or maneuvers can be detected with simple peak detection algorithms that identify high acceleration events. The machine learning

model analyzes the raw IMU signals and GPS data while the vehicle is in motion. With user permission, events that are determined as risky, e.g., events that exceed a g-force threshold or are otherwise classified by the model as risky, are logged along with metadata such as geolocation, vehicle speed, road identifier, timestamp, etc. Such data are provided to a central server (216) that maintains a database (220) of driving events. By processing the data from sensors locally on the smartphone and only logging specific events that are identified as risky, bandwidth and storage resource usage can be minimized.

Using the geocoded driving events that are stored in the database, a risk map (218) is generated and sent to a navigation module (212) of the application. The risk map includes events overlaid on top of a road network to show accident hotspots. The driving events can also be analyzed based on environmental factors such as time of day, weather, road geometry, etc. Thus, using the techniques of this disclosure, scenarios that are highly correlated with unsafe driving events (e.g., a combination of low visibility, bad weather, sharp turn, as described in Fig. 1) are identified. Such identification is used for safety features, e.g., providing routing advisories, dynamic UI alerts, etc., via the navigation module of the mapping application. Further, risky driving scenarios can also be mitigated by developing new Advanced Driver-Assistance Systems (ADAS) capabilities such as vehicle intervention.

The described techniques can improve road safety by focusing on detecting unsafe driving events that occur more frequently than collisions and that are symptomatic of road safety in general. Implementing the prediction techniques on a network of smartphones (e.g., as part of a mapping and navigation application), as permitted by respective users, the described techniques enable large-scale measurement of road safety that is more complete and richer than that based on collisions alone.

Further to the descriptions above, a user is provided with controls allowing the user to make an election as to both if and when systems, programs, or features described herein may enable collection of user information (e.g., information from sensors of a user device, a user's current location), and if the user is sent content or communications from a server (e.g., risk map). In addition, certain data are treated in one or more ways before it is stored or used, so that personally identifiable information is removed. For example, a user's identity is treated so that no personally identifiable information can be determined for the user. Thus, the user has control over what information is collected about the user, how that information is used, and what information is provided to the user.

CONCLUSION

To improve overall trip smoothness and safety while in a vehicle, with user permission, the techniques of this disclosure utilize environmental factors (e.g., road geometry, weather, narrow lanes, etc.) and identify risky driver actions (e.g., speeding, sharp deceleration, etc.) to predict the likelihood of an unfavorable driving outcome. With user permission, dangerous driving maneuvers are identified using data from inertial sensors such as the accelerometer, gyroscope, and magnetometer, e.g., on a smartphone or other device in the vehicle. A machine learning model, provided as part of a smartphone application, such as a mapping and navigation application, is utilized to analyze the data obtained from the inertial sensors. Results from the machine learning model are used for mitigation strategies such as routing advisories, dynamic UI alerts, refinement of driver assistance features, etc., designed to reduce or eliminate unfavorable driving outcomes.

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