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Research Article

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A system proposal to reduce road traffic accidents using smart phones

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Abstract Traffic accidents cause huge damages on human life, and economy. Ubiquitous emergence of smart phones, and IoT (Internet of Things) devices give rise to signal analysis with the embedded sensors and communication of dynamic data. Usage Based Insurance telematics, fleet tracking, driving assistance systems, eco driving and safe driving are among the applications demanding more accurate evaluation of driving skills and driver profiling. Recently there are many studies to evaluate and classify driving skills based on common IMU sensors on smartphones with reasonable results in driving pattern recognition. However evaluation of driving skills require fine granulated approach with collective driving data on the same roadways and similar conditions. Traffic rules, road semantics already regulate safer driving practice. In this study we propose a system which combines road semantics, traffic compliance and smartphone based driving maneuver analysis to improve safety either in the form of a smart black box or as a driving assistance system..

Keywords Driving Analysis, Road Context, Vehicle Telematics, Machine Learning, Advanced Black Box

Introduction

According to a recent report from World Health Organization (WHO) about 1.25 million people die each year as a result of road traffic crashes. More than 90% of these accidents occur in the low and middle income countries although they contribute only 54% of the vehicles in the world [1].Traffic rules are part of the safe system approach to ensure a safe transport system for all road users which eliminates fatal crashes and reduce serious injuries. Major components of this approach are based on safe roads, safe driving speeds, safe road user and vehicles. Implementation of such rules and infrastructure requires elimination of many constrains which are disposed as risk factors. For example, traffic enforcement elements reduce traffic accidents but placing them in all required locations in a road is a major implementation constraint. Vehicle producers design various driver assistance systems (DAS, ADAS) to create a safer driving experience mostly beyond the limits of the drivers' physical capabilities. Unfortunately most useful ones are implemented on recent, higher end cars and lack of road context information.

Ever increasing usage of smartphones provide a pervasive environment for computer assistance for daily life. They provide high speed communications as well as sensor related environmental perception capabilities in an affordable price level for major part of the drivers.

An ADAS system that can be implemented using smartphones or equivalently specified embedded systems, which can also act as a black box safety monitor to extend impact of traffic rules. Due to low cost, low profile requirements such a system can be integrated to all motorized road vehicles. In this paper, solutions for challenging problems to realize such a system are outlined

Roads provide the domain and media for transportation. Traffic signs have been used a sign conveying information, an instruction, or a warning to drivers. Traffic rules imposed or notified by the traffic signs are expected to be attended by the road users to maintain safe driving. Except for the adaptive traffic lights, or dynamic message signs they provide static information about the road, conditions or vehicles sharing the road. As they are not interactive, compliance is checked in limited means *i.e.* overtaking can be forbidden in a certain road segment, this can be informed by a traffic sign, and a "no overtaking" road marking but any vehicle ignoring this cannot be determined unless there is a traffic police monitoring the spot or in case of an accident.

In addition to law enforcement, increasing number of insurance providers reward good driving habits by discounted insurance premium in usage based insurance (UBI) scheme. With the developments on the mobile technologies, companies rate and value risky driving event and habits like distracted driving, over speeding, aggressive driving, tailgating, through smartphone applications and built in cameras. EU imposes compulsory black box regulations to improve traffic safety.

In this study we propose as system which combines ADAS, law enforcement or UBI reporting features and long term memory recording capabilities of a black box system. We will concentrate only on the IMU sensors. Further addition of vision analysis could extend the capabilities like nearby object detection, pre collision analysis.

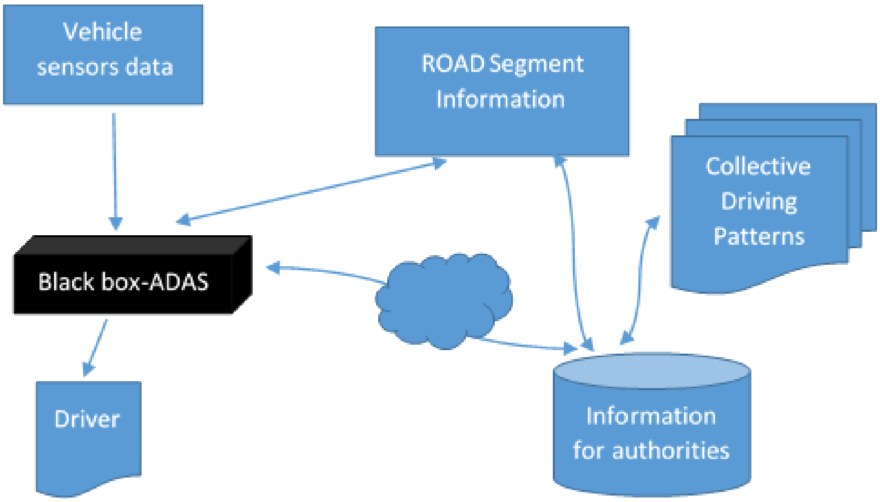

Figure 1: Steps of driving experience analysis

Driving Event Detection

There are many studies in the literature to analyze driving maneuvers using smart phones.

One of the earliest work Nericell, proposed by Mohan [2] uses a Windows Mobile smartphone, to monitor braking events, bumpers, potholes and driver behavior like honking. In his study localization is provided by a GPS sensor, and external accelerometer data within sliding windows is used against empirically defined threshold values.

MIROAD, is an IPhone application proposed by Johnson and Trivedi [3] , uses sensor fusion of magnetometer, accelerometer, GPS and gyroscope to detect aggressive driving events. Driving events are classified for aggressive style patterns using DTW (Dynamic Time Warping), with up to 97% TP accuracy.

Fazeen et al, [4] give driver feedback, after successfully identification of bad driving maneuvers from lane change, acceleration, and braking events from an empirical set of predefined thresholds. In their experiment the smartphone is a fixed position and no coordinate system alignment is required however it is vulnerable to slight changes or vibration.

Eren, Makinist et al., [5], use FastDTW algorithm [6]to compare driving maneuvers , and interpret maneuver patterns in a Bayesian framework.

Castignani et al. [7], propose a driver monitoring and profiling system called SenseFleet based on smartphone sensors with an emphasis on UBI and commercial fleet applications. Driver scoring is realized using a Fuzzy interface.

V-Sense [8] is one of the first precise implementation with lower number of sensors.

They concentrate mainly on classification of driving maneuvers

Smartphone sensors are extensively used in the previous works. Most of them rely on detecting accelerometer sensor events with a predefined sets of empirical thresholds.

Accelerometers, digital compass, and gyroscopes are found almost all of the modern smart phones to provide orientation information.

Out methodology is composed of the following phases:

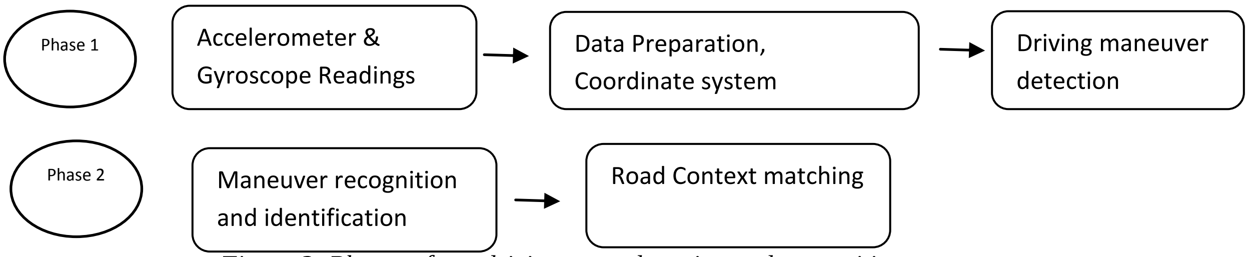

Figure 2: Phases of our driving event detection and recognition process

Many authors in the literature listed, use almost the same techniques for detecting driver maneuvers.

Some of the authors propose sensor fusion using magnetometers. For example MIROAD uses a magnetometer to determine the heading angle for lane changes.

Here we propose a reduced set of sensors, only an accelerometer and a gyroscope data to determine the type of a maneuver.

Recent studies use the same routine operations to detect basic driving maneuvers in detail. They achieve maneuver detection using fewer sensors and a greater accuracy [7, 9, 10].

Instead of repeating the same process, we would like to emphasis on the major challenges in detection of driving events.

Noisy data:

Noise from vibration from the vehicles, or sudden movement in gravity direction can be eliminated by low-pass filters in a linear time.

Arbitrary phone position and orientation:

In UBI, when trip data is requested using a freewill cooperation, smartphones can be in any orientation in a fixed, lose or loosely fixed position.

Many of the experiments are done with a firmly fixed phone, oriented in line with the vehicle coordinate system. However applications like UBI or volunteer auditing for public transit vehicles require more flexibility and versatility by allowing any arbitrary orientation. The smartphone should be in a fixed position although its orientation would be different from the vehicle.

Translating the phone's coordinate system, to car's reference axes is a straight forward application using a rotation vector. After fixing the z direction towards the Earth center, x and y coordinates can be aligned after applying rotation of axes twice. Modern smartphone SDK (Software Development Kits) provide rotation vectors. After an initial acceleration phone can be calibrated.

False data from magnetometer

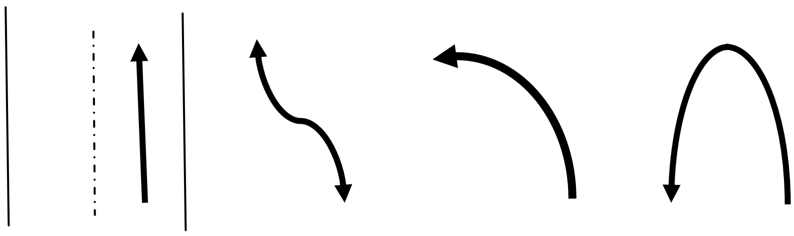

Figure 3: Vehicle's heading angle changes during steering events

Same authors including [10]successfully recognize turn signal sounds even with noisy conditions, which completes detection of maneuvers as classified by NHTSA (United States Department of Transportation).

Table 1 :Classification of Driving Behaviors by NHTSA Source [10]

No.	Names	Description
1	Normal turns	Normal maneuvers of turns
2	Normal lane-changes	Normal maneuvers of changing lanes
3	Normal U-turns	Normal maneuvers of U-turns
4	Sudden turns	Sudden turns with turn signal on
5	Sudden lane-changes	Sudden lane changes with turn signal on
6	Sudden	U-turns Sudden U-turns with turn signal on
7	Turns without scruple	Normal turns or Sudden turns with turn signal off
8	Lane-changes without scruple	Normal lane-changes or Sudden lane-changes with turn signal off
9	U-turns without scruple	Normal U-turns or Sudden U-turns with turn signal off

Once the elementary maneuvers are detected, we need a model which defines whether application of these maneuvers are compatible with the interests. Interest would be any framework including traffic rules compliance, UBI, and eco driving.

Road Semantics

Roads are designed in conjunction with design guidelines and standards imposed by international and national authorities. The physical elements of roadways are geometrically placed by taking into account speed, vehicle type, road slope, view obstructions, and stopping distance.[11]

Roadways can be considered as semantics structures which provide information about themselves. Semantic elements are presented in the form of general traffic rules, and visual elements like static or dynamic traffic signs.

Roadway conditions vary with multitude of different constrains. Physical conditions dictate the main traffic rules such as geolocation, road structure, junctions, width, length, and the proceeding road segments.

Additionally traffic regulation rules introduce newer constrains like traffic flow direction, speed constrains, take over constraint, allowed turns, distance from traffic adjustment points. Some of the rules can also be valid under certain weather conditions, or certain periods, like school hours, road work period deviation.

Once the semantic structure of each segment defined in an easily accessible way driving assistance for forthcoming conditions can be provided easily.

With the availability of the high speed inter service on the roads and built-in GPS sensors, mobile navigation applications do provide not only the most suitable route for a selected destination, but also the most efficient, cost effective or quickest ones based on the dynamic traffic information collected by other active agents using the route. These navigation maps use general road geometry information including junctions and relation to other nodes, and traffic flow direction. Recently services like Google Maps [12], Yandex Maps[13] , Waze [14] provide dynamic routing feature. However their main interest is reaching a selected destination using one of the route options delivered. Dynamic maps can correctly address issues like traffic jams, roads under construction. However since their primary purpose is not traffic regulation they include only minimally required features lake lane assistance to recommend timely warning before lane related actions like junctions, exits in the highways.

There are many studies to locate and recognize traffic light positions [15-17]. Some of them make use of cameras to recognize the location of the traffic signs, lights. Although such systems provide good detection scores they are vulnerable to vision conditions.

Some of the authors introduce sensor fusion techniques to identify in lane position. In the previous chapter, we already have done some localization in a lane by detecting the lane changing, and overtaking maneuvers.

As a black box system for traffic enforcement our interest is compliance with the traffic rules. Road users are informed about the valid traffic rules in the current or next segment by traffic signs and traffic signs positions do not change in timely manner because they are mostly bound with road geometry and common conditions.

Using this fact into consideration we propose a built in road maps with annotated traffic conditions.

Once these ontological features are defined in a map they can be presented as semantic conditions related to the geographical location of the car.
Microsoft provides OpenStreetMap [18] an open source, community driven, customizable map.
Traffic sign positions, lane constraints such as divided road, shared road, traffic flow directions, safety lane, lane users, priority lane, number of lanes, forthcoming junction sites, speed regulations within the segment, traffic sign type like school crossing, can easily be integrated to such a map.
Such maps consume storage space which is not an issue for a recent smartphone. A metropole city like Istanbul takes up only 23 MB storage, while it would be possible to reduce this size only using the road geometry and traffic rule related features.
Some of the features require precise localization of traffic signs, however road signs are designed to inform driver's navigation at normal speeds and therefore leave enough space within the limits of GPS accuracy.
Lane identification or correct in lane positioning would be required for a more precise application of some overtaking rules.

Driving Pattern Analysis
In a black box recording application, events are analyzed retrospectively. In our extended map, a junction is defined as a roadway segment. When the vehicle enters a junction segment localized with GPS coordinates all the preceding maneuvers are evaluated. As an example, if the junction segment does not allow left turn, the event it is directly reported as a traffic rule infringement. If the context allows a left turn, in-lane positions, or a sudden change in the heading to move to the correct lane is controlled. Before the turn,turn signal sound is checked and according to the context, proper turn sequence is checked. For example in the US a full stop and checking the traffic is required if a traffic light is not present.

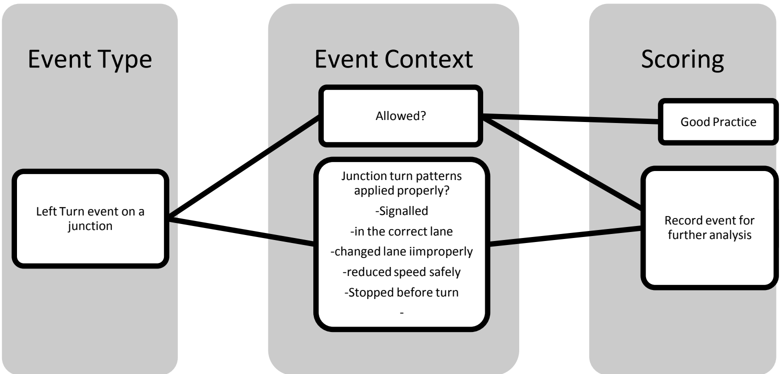

Figure 4: Retrospective decision tree example for a turn event

Many driving events patterns can be classified in a similar fashion.

Table 2: Event context conditions check patterns for some driving events.

Event	Event Context Checks
Acceleration	○ Speed limit exceeded? ○ Speeding duration and context, frequency, ○ speed value
Sudden stops	○ Number of stop events in a period, ○ Tailgate patterns (stopping to and accelerating too often)
Lane changes	○ Is lane changed allowed in the context? ○ Is lane acceptable for this vehicle type, ○ Performance of the lane change (sudden change) ○ Turn signal activated?

	○ Frequency of the lane changes ○ Lane change restrictions according to current lane (like occupying the left most lane constantly)
U-Turn	○ Is U-Turn allowed in the road segment?
Regular driving	○ Allowed direction in the road context ○ Allowed Lane? ○ Cared for traffic lights warning, school, junction ○ Occupying the speeding lane?

This table can be augmented with every time of driving events, road context, circumstances as well as traffic rules imposed by the local authorities.

Driving Behavior Classification

In the relevant literature listed in the previous section, drivers' performance are judged by just the driving skills against to some statistically acceptable correct patterns by Bayesian or Fuzzy inferences, or some other machine learning methods. However main factor in the traffic that maintains the safety is traffic rules. In the approach we accept drivers as cooperative agents, willing to share traffic with the regulations. The algorithms depicted just makes a retrospective analysis to score this match.

Not every driver is follows the most legal driving patterns all the time. In this case, classification can be done on the same conditions in that segment, and among the drivers in the long term.

In addition to traffic enforcement a similar scheme can be applied for other profiles such as safety, insurance, eco driving, purpose of the vehicle.

Unlike the previous solutions we base our scoring references to following classes for a more fair and meticulous evaluation:

- Collective patterns
- Persons driving patterns dataset
- Dynamic Context information

The system we proposed can be used with various motivations for different applications. Drivers of public transit vehicles would have more strict legal compliance or passenger comfort priorities with schedule constrains. Scoring for them would include compliance list such as efficiency or anticipation.

Efficiency measures can be based on the magnitude and duration of the events; i.e. the G-force encountered by the driver and his passengers while accelerating or braking, and the centripetal force encountered during turns.

Insurance telematics, or fleet management would require evaluation scheme based on anticipation that is the time between subsequent events. Anticipation represents how smooth a user drives, and models his ability to anticipate traffic conditions. The anticipation score represents sequences of events, such as braking before versus during a turn, coasting versus braking in front of a traffic light, etc.

Rush hour traffic would dictate a different efficiency patterns. Weather conditions, semantic states of the drivers would have a strong impact on the driving experience.

Collective driving data ensure more fair evaluation of driving data, within the conditions of most of the other users of the same road segment in the same time frame.

Legal Compliance for safe driving:

Some of the important and high priority events can be recognized after detecting maneuvers within the road segment context. For example dangerous driving like zig-zag driving, driving in the wrong direction, incompliance with the stop rules at junctions, or exceeding speed limits can be tagged as high priority data.

Conclusion

The system we propose here demonstrate that even low cost sensor platforms such as smartphones can help to reduce traffic accidents by forcing drivers to comply with the safe, proper and legally allowed driving practices. Here motor vehicles equipped with the black box system we recommend, would act as both a driver assistant and a full time traffic police.

Addition of some more smart sensors like LIDAR, 3D cameras would bring additional features but our purpose is a simple aftermarket addition to existing vehicles to reduce traffic accidents.

In some cases a more precise dead reckoning and lane level estimation would improve efficiency of the system.

References

[1]. WHO. (http://www.who.int/mediacentre/factsheets/fs358/en/). 2017 [cited 2017 7/20/2017].

[2]. Mohan, P., V.N. Padmanabhan, and R. Ramjee, Nericell: rich monitoring of road and traffic conditions using mobile smartphones, in Proceedings of the 6th ACM conference on Embedded network sensor systems. 2008, ACM: Raleigh, NC, USA. p. 323-336.

[3]. Johnson, D.A. and M.M. Trivedi. Driving style recognition using a smartphone as a sensor platform. inIntelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on. 2011.

[4]. Fazeen, M., et al., Safe Driving Using Mobile Phones. Intelligent Transportation Systems, IEEE Transactions on, 2012. 13(3): p. 1462-1468.

[5]. Eren, H., et al. Estimating driving behavior by a smartphone. inIntelligent Vehicles Symposium (IV), 2012 IEEE. 2012.

[6]. Salvador, S. and P. Chan. FastDTW: Toward accurate dynamic time warping in linear time and space. inKDD Workshop on Mining Temporal and Sequential Data. 2004. ACM.

[7]. Castignani, G., et al., Driver Behavior Profiling Using Smartphones: A Low-Cost Platform for Driver Monitoring. Intelligent Transportation Systems Magazine, IEEE, 2015. 7(1): p. 91-102.

[8]. Chen, D., et al., Invisible Sensing of Vehicle Steering with Smartphones, in Proceedings of the 13th Annual International Conference on Mobile Systems, Applications, and Services. 2015, ACM: Florence, Italy. p. 1-13.

[9]. Ferreira, J.J., et al., Driver behavior profiling: An investigation with different smartphone sensors and machine learning. PLOS ONE, 2017. 12(4): p. e0174959.

[10]. Liu, X., et al., A Vehicle Steering Recognition System Based on Low-Cost Smartphone Sensors. Sensors, 2017. 17(3): p. 633.

[11]. (https://en.wikipedia.org/wiki/Geometric_design_of_roads). 2017 [cited 2017 07].

[12]. Inc., G. maps.google.com. 2017 [cited 2017 07].

[13]. Yandex. maps.yandex.com. 2017 [cited 2017 7].

[14]. Inc., W. waze.com. 2017 [cited 2017 7].

[15]. Ren, F., et al., Lane Detection on the iPhone, in Arts and Technology: First International Conference, ArtsIT 2009, Yi-Lan, Taiwan, September 24-25, 2009, Revised Selected Papers, F. Huang and R.-C. Wang, Editors. 2010, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 198-205.

[16]. Tao, Z., et al. Lane marking aided vehicle localization. inIEEE 16th International Conference on Intelligent Transportation Systems (ITSC 2013). 2013. Hague, Netherlands.

[17]. Toledo-Moreo, R., D. Betaille, and F. Peyret, Lane-Level Integrity Provision for Navigation and Map Matching With GNSS, Dead Reckoning, and Enhanced Maps. IEEE Transactions on Intelligent Transportation Systems, 2010. 11(1): p. 100-112.

[18]. OpenStreetMap.org. (https://en.wikipedia.org/wiki/Geometric_design_of_roads). [cited 2017 07].