Knowledge-based Real-Time Car Monitoring and Driving Assistance

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Abstract. This paper describes a knowledge-based framework for a driving assistance via smartphone. Vehicle information extracted through On Board Diagnostics (OBD-II) protocol, data acquired from smartphone embedded micro-devices and information retrieved from the Web are properly combined. Data fusion and classification algorithms allow to identify and annotate relevant contexts and events in real time and semantic-based matchmaking is exploited to infer dysfunctional situations.The proposed approach has been implemented in an Apple iPhone application, and evaluated in real-world test drives.

Keywords: Semantic Web, Ubiquitous Computing, Data Fusion, On-Board Diagnostics, Intelligent Transportation Systems

1 Introduction

Modern vehicles are equipped with several Electronic Control Units (ECUs) coordinating and monitoring internal components and subsystems, communicating over one or more car network buses. In particular, international regulations today mandate all new vehicles must support the *On Board Diagnostics, version 2* (OBD-II) protocol (http://www.arb.ca.gov/msprog/obdprog/obdprog.htm) and be equipped with an OBD-compliant interface to provide direct and standard access to data in the internal automotive network. Furthermore, in case of malfunctions, Diagnostic Trouble Code (DTC) values are stored in the car ECU and can be later retrieved by maintenance technicians using proper tools. Recently, access has been granted also to the general public of car enthusiasts by the development of OBD-II *scan tools*, cheap electronic devices that bridge the OBD-II port with standard wired (RS-232, USB) or wireless (Bluetooth, IEEE 802.11) computer communication interfaces.

This paper enhances framework in [1], able to interpret vehicle data extracted via OBD-II, integrate environmental information and detect potential risk factors. Beside providing warnings for that, now the system gives suggestions during driving and evaluates car efficiency and environmental impact. It is fully compliant with widely available smartphones.By means of properly devised processing and fusion algorithms, the system is able to identify and classify given

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high-level events and conditions, based on low-level data streams. Furthermore, leveraging Semantic Web languages and technologies, events are annotated w.r.t. an ontology that models characteristics influencing driving safety and undergo a matchmaking process –exploiting an embedded matchmaker supporting non-standard reasoning services [2]. The matchmaking outcome is used to suggest the driver (via her smartphone) actions and behaviors she should adopt. The proposed framework has been implemented in a prototypical mobile software system, using the Apple iPhone[1] smartphone as reference platform. The experimental evaluation has been carried out in several real-world test drives under different conditions, evidencing both feasibility and usefulness of the approach.

In the remaining of the paper, after a survey on relevant related work in Section 2, the proposed framework is described in Section 3. Tests corroborating the approach are presented in Section 4. Conclusion and future work close the paper.

2 Related Work

Literature about OBD-based systems for vehicle monitoring and alert refers to *remote* and *on-board* solutions, respectively. In the former type [3, 4], GPS data and vehicle OBD DTCs are sent to a Maintenance Center server via GPRS/UMTS and stored into a database, which is scanned by a diagnostics expert system that generates a rough suggestion to advise the maintenance technicians. The proposal presented here does not require experts to evaluate system outputs. Furthermore, information processing refers to a smartphone application and then it better resembles an on-board approach. Consider that, though useful for managing vehicle fleets, remote monitoring does not allow a direct driver assistance. Several on-board monitoring prototypes and reporting systems have been already proposed [5, 6]. Nowadays freeware and commercial software packages are available, that allow to monitor OBD-II vehicle data by using just a smartphone and off-the-shelf scan tools. Nevertheless, to the best of our knowledge, all existing on-board monitoring systems directly display the acquired low-level data. They do not analyze the information to provide more meaningful and user-friendly indications, though researchers have widely acknowledged the possibility to exploit the wealth of real-time vehicle data available trough OBD in order to analyze driver behavior [7]. Current efforts aim to use multi-source information fusion to better interpret the relationships between driving habits and vehicle performance, as well as to detect risk situations [8]. Nevertheless, in available works analysis is performed off-line after data gathering, so they are not able to provide an automatic real-time driver support.

3 Framework

Starting from [1], the proposed system monitors a larger set of parameters, including environmental conditions, gas emissions, fuel consumption, engine load,

[1] iPhone Specifications, http://www.apple.com/iphone/specs.html

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vehicle performance, safety equipments status and driving style. The *Kiwi Wifi*[2] wireless adapter interfaces car ECUs via OBD-II. When turned on, it builds an IEEE 802.11 ad-hoc network exposing a static IP address allowing an application to communicate with the OBD interface via socket in read/write mode. The proposed approach works along three subsequent stages: (i) data gathering; (ii) data fusion; (iii) semantic characterization and matchmaking. They are repeatedly executed; after each data gathering, further steps are executed and outcomes are displayed on the iPhone screen added to audible alerts.

Data gathering. As described in [1], OBD-II specifications only comprise the *Physical Signal Layer* (PSL) and *OBD-II Data Communication Layer* (DCL) of the ISO/OSI model. Though the system is able to retrieve all possible vehicle parameters via the OBD-II interface, our analysis focused on: coolant temperature, engine load, throttle position, RPM (Revolutions Per Minute), vehicle speed, MAF (Mass Air Flow), fuel level, upstream and downstream oxygen sensor. Considering wireless communication latency between the *Kiwi Wifi* PLX and the iPhone, the system requests a parameter every 0.3 seconds. Through the iPhone GPS receiver, the system gets latitude and longitude of vehicle current position, which are used to collect information about location address, road type and weather conditions via HTTP requests to Web services [1], using mobile Internet connectivity.

Data fusion. Previously collected data are processed at this stage to identify conditions and events to be annotated w.r.t. a reference ontology. The selected data fusion techniques provide adequate sensitivity for our purposes, while also maintaining moderate computational and memory requirements. Along with road features, driving style and traffic, as in [1], now the system can detect the following additional conditions. ***Emissions.*** To comply with emission regulations, OBD requires at least two oxygen sensors to evaluate the efficiency of catalytic converter for gasoline engines: an upstream and a downstream one. They provide feedback for maintaining the proper fuel mixture for efficient combustion and regular emissions, respectively. Each oxygen sensor produces a voltage value between 200mV and 900mV depending on the amount of hot oxygen it is exposed to. 15 samples at a time are considered also counting samples exceeding 900mV (MAX) and samples smaller than 500mV (MIN). This threshold was chosen because maximum voltage basically range from 500mV to 900mV, instead minimum voltages at most reach 500mV. In this way, for the upstream oxygen sensor, we infer that if $|MAX - MIN| < 5$, combustion is regular, otherwise not. For the downstream oxygen sensor, if $|MAX - MIN| > 9$, emissions are regular, otherwise not. ***Gear setting.*** A right use of gear lever is revealed measuring the ratio of throttle position (expressed in percent) to the engine load. Tests proved that in case of proper behavior the ratio value is around 1. A value greater than 2 indicates the user is requiring a power the engine cannot provide. The system computes the integral area of the throttle/engine load ratio considering 7 samples at a time. If the threshold value of 7.7 is exceeded, a wrong gear lever is detected. ***Fuel consumption and autonomy.*** Fuel consumption computation

[2] PLX Devices, Kiwi Wifi, http://www.plxkiwi.com/kiwiwifi/hardware.html

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is based on MAF, *i.e.*, the mass of air (in grams) entering the engine every second. Then the volume of injected fuel (l/s) is:
$injected\_Fuel = MAF \div (fuel\_Factor \times fuel\_Density)[l/sec]$
where $fuel\_Factor$ is the stoichiometric ratio of air to fuel (equal to 14.7) and $fuel\_Density$ is the fuel density at 15°C (720 g/l for gasoline). Dividing vehicle speed by injected fuel, fuel consumption (in km/l) is obtained, from which average consumption and autonomy are computed.

Semantic annotation and matchmaking. The semantic annotation prepares the subsequent matchmaking phase. A toy ontology (not reported here for brevity) has been implemented in OWL-DL (Web Ontology Language, W3C Recommendation, http://www.w3.org/TR/owl-features/) formal language, grounded on Description Logics (DL) semantics. Their main classes are: **Vehicle** with subclasses *Safety_Equipment* and *Sensor*. **Safety_Equipment** is specialized in: *Fog_Lamp*, *ABS*, *ESP* and *Snow_Chains*. **Sensor** has subclasses: *Speedometer*, *RPM_Sensor*, *Fuel_Level_Sensor*, *MAF_Sensor*, *ThrottleLoad_Ratio*, *PreOxy_Sensor*, *PostOxy_Sensor*. Other classes are **Weather**, **Road_Surface**, **Road_Condition**, **Traffic**, **Driving_Style**. Main roles are: **hasDriving_Style**, **hasSafety_Equipment**.

While [1] relied on a remote matchmaking engine accessed via HTTP, here an Objective-C version of the Java mobile matchmaker described in [9] is exploited. This avoids dependence on cellular data connection and centralized reasoners, so improving significantly system reliability, latency and bandwidth consumption. The *Concept Abduction* non-standard inference was selected as reference reasoning service [2, 9]: in a nutshell, given a request R and a provided resource/service S, described w.r.t. a shared ontology, Concept Abduction allows to identify what is missing in S in order to completely satisfy R. In our framework, the semantic annotation of the context and the semantic description associated to an optimal vehicle functioning represent the request (*i.e.*, what factors are needed to travel safely and efficiently), while the semantic description of vehicle actual status and user driving style are the provided resource (*i.e.*, what factors are provided by the “vehicle+driver” system). Hence, the Abduction process will infer every requirement needed for a correct vehicle condition not explicitly satisfied by current vehicle configuration and driver behavior. Thus proper suggestions are provided to the driver in order to prevent dangers and/or reduce inefficiency. For example, let us suppose to monitor the level of vehicle exhaust gas emissions in a high density traffic situation. The semantic-based request for the system is (in DL formalism and w.r.t. the above cited ontology):

$$R \equiv Emission \sqcap \forall\ hasSensor\_PreOxy.Normal\_PreOxy \sqcap \forall\ hasSensor\_PostOxy.Normal\_PostOxy \sqcap Traffic \sqcap \forall\ hasSecure\_Device.ABS \sqcap \forall\ hasSensor\_Speed.Low\_Speed \sqcap \forall\ hasDriving\_Style.Even\_Pace\_Style.$$

It means that to have a low level emission and to avoid risks produced by an high density traffic, the output signals of upstream and downstream oxygen sensors should follow the above patterns, the vehicle should be equipped with ABS and the user should adopt an even pace driving style with low speed. Let us suppose the actual “vehicle+driver” system, *i.e.*, the provided resource is:

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Fig. 1. Application user interface

$S \equiv Vehicle \sqcap \forall\ hasSensor\_PreOxy.Normal\_PreOxy \sqcap \forall\ hasSensor\_PostOxy.Abnormal\_PostOxy \sqcap \forall\ hasSecure\_Device.ESP \sqcap \forall\ hasSensor\_Speed.Low\_Speed \sqcap \forall\ hasDriving\_Style.Imprudent\_Style.$

By applying the abduction process to R and S:

$H \equiv \forall\ hasSensor\_PostOxy.Abnormal\_PostOxy \sqcap \forall\ hasSecure\_Device.ABS \sqcap \forall\ hasDriving\_Style.Even\_Pace\_Style.$

Hence, the system detects an abnormal output signal from the downstream oxygen sensor, indicating irregular exhaust gas emissions; moreover high traffic density suggests the need for ABS, as well as to adopt moderate drive. Since the vehicle only offers ESP and the user drives imprudently, the abduction outcome suggests to activate ABS and adopt an even pace driving style to decrease risks. Notice that, due to the Open World Assumption, semantic matchmaking –differently form database queries or rule-based engines– allows meaningful results to be inferred also in case of incomplete information (*e.g.*, lack of sensors on specific car models or temporary unavailability of data).

4 Experiments

The proposed framework was implemented in a system prototype for testing the approach.The test route was composed by: (i) a 3 km fast-flowing road; (ii) a 5 km fast-flowing stretch of an high speed road; (iii) a 2.5 km uphill stretch of a moderate speed road; (iv) a 3 km slow-flowing road. The test car, registered in 2001, is fueled with gasoline. At the application start-up, user can activate monitoring via the GUI whose main view is in Figure 1. After few seconds the icons in the *ADVICE* section are colored in function of matchmaking results. The application emits a single audio signal when an icon changes from green or yellow to orange, a double audio signal when it changes from orange to red so indicating different alert levels. Although quantitative performance measures were not taken at this stage of the work, system outcomes were globally coherent with the real driving situations and suggestions provided to the driver were appropriate. Warnings were sometimes issued with few seconds delay due the time needed to acquire the samples. These preliminary tests showed that

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careful design and optimization allow semantic-based tools to be run in real-time on current mobile devices. By combining efficient data fusion algorithms and optimized semantic inference procedures, our approach can achieve both precision in condition detection and high-level information characterization for added-value driver support services.

5 Conclusion and Future Work

The paper presented a framework and a prototypical system for real-time vehicle monitoring and driving assistance. Information extracted via OBD-II, from smartphone micro-devices and Web services is used to annotate the context for further semantic-based inferences. Future work includes enhancements to the mobile prototype, *e.g.*, voice alerts and, as far as research is concerned, further OBD parameters and smartphone peripherals (*e.g.*, camera, microphone) could be used and concrete domains included in reference logic languages.

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