Towards a "Holistic" Safety Monitoring in Intelligent Vehicle Control

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Abstract: Today, the state of the art in vehicle safety follows an explicit design flow. Specific sensors measure a particular dimension (e.g. distance to other vehicles) and "safety" is defined as a specific range of allowed values (e.g. minimal distance). The disadvantage of such an approach is that safety issues which were unconsidered at design time are not detectable. Furthermore, a detection of issues that are only indirectly measurable is difficult to realize. In this paper, a holistic safety monitoring approach is presented that makes use of all available sensor data and tries to find an implicit definition of "safety". By such an inverse approach vehicle safety issues which are hard to be directly measurable might be detectable, too. For instance, an identification of driver-initiated critical situations (e.g. caused by distraction) could be possible if taking multiple sensor modalities into account and having an implicitly defined "safe" state.
Furthermore, the article describes the selection of potential test platforms and shows already collected test data of a mobile robot platform. Presented in this work-in-progress paper is the concept of definition, implementation, and detection of implicit vehicle safety.

1 INTRODUCTION

Intelligent vehicle safety mechanisms are currently following an explicit design: safety is designed explicitly in specific modalities. For example, distance sensors measure explicitly the distance to other vehicles or obstacles in the vicinity and "safety" is defined as a certain minimum distance related to the current speed. For lane-keeping assistants and airbags it is the same, having "safety" defined as certain thresholds of distances/angles or accelerations, respectively.

While these methods ensure a safe state in the respective modality, the question arises if a general, multi-modal definition of safety is possible (and detectable), too. The point is that on the one hand side a combination of several slightly increased safety measures may – altogether – indicate a critical safety issue while on the other hand a single threshold exceeding might be tolerable. Besides, such a "holistic safety monitoring" could perhaps even cover cases which are not known at design time. As the driver's behaviour influences the system and its sensor readings, it could be possible (up to a certain extent) to detect driver-initiated safety issues, too.

Furthermore, in single-modality setups a drop out of a single sensor is a potential cause for a "false-positive" triggering of a safety mechanism or for a "false-negative" rejection of executing safety means. Addressing such drop-outs, the field of fault detection, isolation, and recovery arose. Here, implicit or explicit models are used to generate predictions (expectations) of monitored sensor states. By the difference between expectation and measured value, misbehaviour can be detected. Using a (learnable) model for multi-modal predictions and a multi-modal evaluation is a candidate for a holistic safety monitoring.

In the following two sections, related work and a proposition for a holistic safety monitoring system is described. In section 4 sample data of a mobile robot is shown. The section 5 presents potential vehicles to test the proposed system. In the last section a conclusion and an outlook are given.

2 RELATED WORK

One typical class of vehicle safety systems focuses on the detection of particular safety-harming conditions. In case of detection, either the driver is warned or the system triggers a fixed pre-defined countermeasure.

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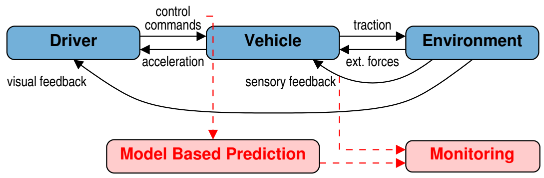

Figure 1: Overview of the proposed safety monitoring.

A recent example for this class is the pedestrian detection method presented by Van Beeck et al. in 2012 (Van Beeck et al., 2012).

A learned generation of expectations of sensor consequences was published by Pastor et al. (Pastor et al., 2011). Based on sensor training data, expectations (mean and variance) are learned. The application presented in that publication is a manipulating two-arm robot.

In the field of fault detection and identification several model-based approaches have been presented. The specific case of combining multiple sensor modalities and learning the model was studied, too (Köhler et al., 2013). But the objective in approaches like that one is different: There, a fault, e.g. drop out, of a part of the system is to be detected while in vehicle safety monitoring a certain state or range of states in correct sensor readings is to be found. However, the proposed methods for fault detection are good candidates to be adapted for the application of vehicle safety monitoring.

3 LEARNING AND EVALUATION OF VEHICLE STATE

The main components needed for the proposed safety monitoring are a) a learnable and multi-modal model, b) predictions ("expectations") based on the model, and c) a monitoring and triggering mechanism to detect "unsafe" or "unusual" conditions. In figure 1 the single components are depicted.

Different methods of model and expectation generation have been studied in previous work (to be published). These methods have been tested on a four-wheeled mobile robot. Their application to a human-driven vehicle needs to be tested. However, the sensor modalities used there are a subset of the modalities to be used in a vehicle safety system (see sections 4 and 5). Examples of such explicit vehicle safety systems are anti-lock braking system (ABS), electronic stability control (ESC), traction control system (TCS) / anti-slip regulation (ASR), airbag, intelligent speed adaptation (ISA) / distance warning / distance control, lane departure warning system (LDWS) / lane keeping assist, and driver attention monitor. These systems use single sensor modalities and are designed aiming for a particular unsafety condition (and triggering a particular safety measure). The sensor modalities needed in the mentioned examples are wheel speeds, accelerations and gyroscopes, distance sensors, and cameras. These are typical candidates for the "sensory feedback" data in figure 1.

Figure 2 shows two different modes of using models for the prediction and monitoring. In mode 1, the model covers the loop from the control commands to the sensor feedback. Commands given by the driver are used to generate expectations of the sensor feedback. The monitor compares these predictions with the actual measurements of the sensors.

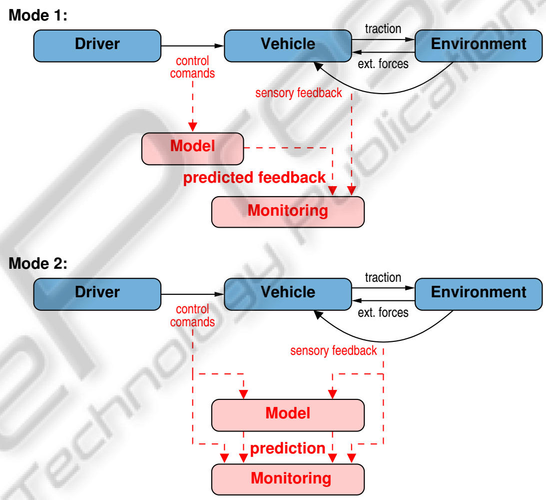

Figure 2: The proposed safety monitoring could be run in two different modes.

In mode 2, the commands and the sensor feedback are used to generate an estimation derived from the learned model. Furthermore, the model generates expectations for the sensor readings and the motion commands. The expectation of motion commands can be used to identify unusal driver behaviours.

In both modes, the monitoring can be realized by either a distance computation (e.g. euclidean distance of normalized vectors) and comparison with a fixed threshold or a standard deviation based adaptable threshold.

Model-based prediction and monitoring can be used targeting different objectives. One possibility is, to have a particular detection (and potentially reaction) in mind. As an example, a model trained to a specific driver's steering, accelerating, or breaking behaviour can be used to detect conditions where additional steering forces or a virtual "kick-down" is applied for comfortability purposes, or an emergency breaking is triggered earlier then standard if a driver usually tends to be more conservative when decelerating.

A second possibility is to target a specific device or function but to not define the unusual/unsafe case (and neither the appropriate reaction). An example is to monitor a specific device like the battery of an electric vehicle (EV). However, the model is trained with the usual normal operating behaviour (in case of the battery in terms of voltage, current, temperature). This example is selected as a use-case described in section 4.2.

Finally, the third possibility is to take multiple or all available (sensor and acutator) modalities to train the model with usual, i.e. normal, expected behaviour. After learning the model, deviations from expectations could be detected – independend of the reason for the deviation and without any knowledge needed at design time.

4 EXAMPLARY EXPERIMENTAL DATA

First experimental results have been collected with a mobile robot platform. The robot is not comparable to combustion-engined or electric vehicles in terms of size, weight, typical and maximum velocities, and typical and maximum accelerations. However, it serves as a first testbench for the study and selection of potential sensor modalities.

To test the methods and sensor modalities studied on the mobile robot, different vehicle platforms are proposed (see section 5). As a first demonstrational use-case, a battery defect or battery handling error of a standard electric vehicle (EV) is chosen.

4.1 Motion Test Data of a Mobile Robot

Three methods for model generation and prediction have been tested in previous work (to be published). The test setup used was a four-wheeled and skid-steered mobile robot. As sensors wheel encoders, accelerometers, and gyroscopes were used.

In figure 3 example data of a turning of the platform is shown. As can be seen, a change of the motion command (e.g. starting to turn) is followed by changes in the different sensor modalities with potentially varing latencies. The sensor response behaviours may depend on vehicle-related parameters (weight, load, engine power, technical malfunctions) or external conditions (environment, street conditions, obstacles).

For the second plot in figure 3, the sensor data of multiple turning trials have been used to train a model of the actuator–sensor relationship. Based on

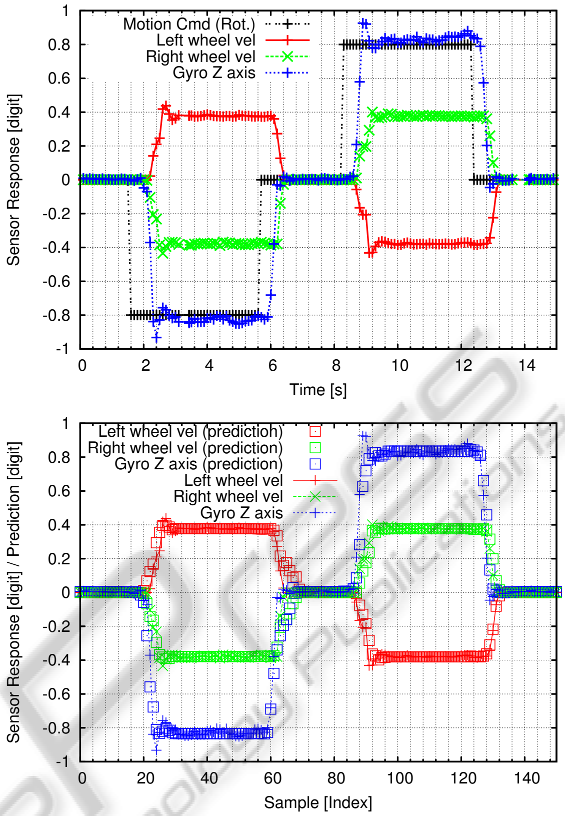

Figure 3: Example plot of measured and predicted sensor data of a turning mobile robot.

the learned model predictions, i.e. expectations, of the sensor responses are generated and are plotted alongside the real measured data in the plot on the right. Depending on the method used to generate the model and depending on its parameters, expectations and measured sensor values match better or worse. The results of different methods and test conditions have been compared in previous work.

4.2 Test Case Scenario: EV Battery

For electric vehicles the battery is one of the parts being most crucial for the vehicle's function. Due to the fact electric drives are more robust and simpler than combustion engines they do not need an as extensive monitoring as combustion engines demand. On the other hand, the batteries used in electric vehicles are more complex than their siblings used in combustion engine vehicles.

The values to be monitored for a proper operation of the vehicle differ a lot (in selection and behaviour) between common combustion engines and electrically driven ones. Whereas in combustion engines the values to be monitored, e.g. fuel level, oil

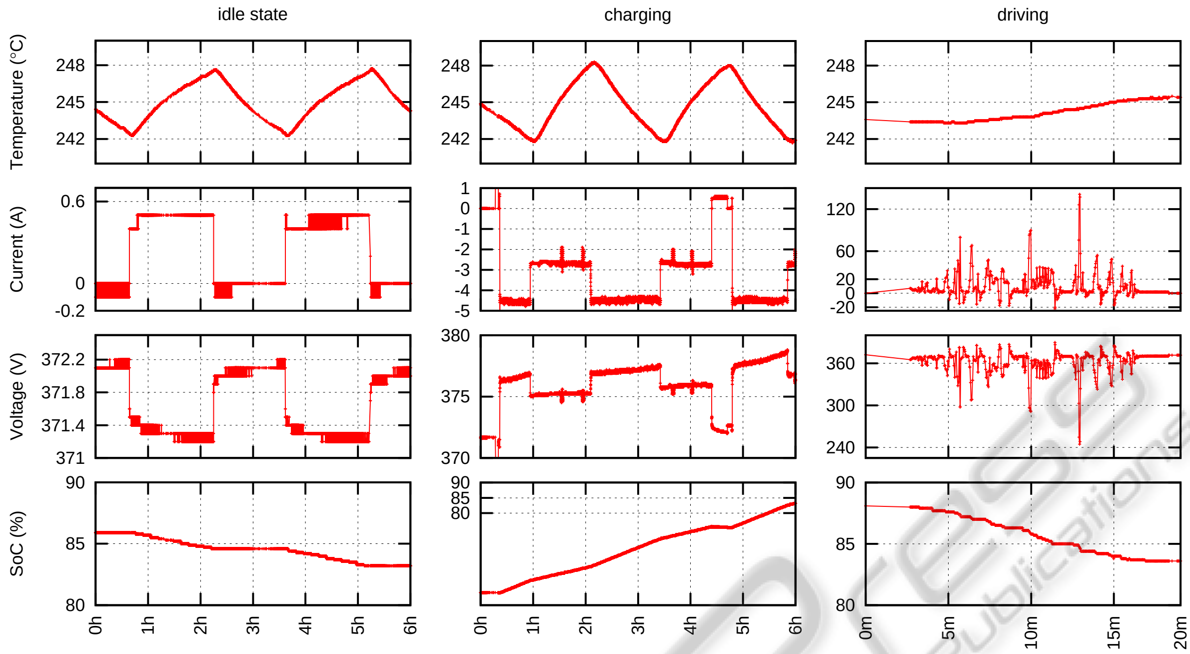

Figure 4: Values measured for an electric vehicle's traction battery (Na-NiCl) in various operation states.

pressure, and motor temperature do only vary slightly in a proper operation, therefore mostly have to be monitored for being within certain boundaries, the corresponding values of a traction battery in an electric vehicle, e.g. battery state of charge, voltage, current, and temperature tend to show a lot more variance – even in idle states (see figure 4).

This is due to the fact that (depending on the type of battery) certain values have to be kept inside certain ranges for a proper operation at all times. E.g., the Na-NiCl battery whose data is depicted in figure 4 has to maintain a certain operation temperature (approx. 245 ° C), so even in idle states there has to be a certain flow of current (for the corresponding battery heating element). This load also has an influence on the voltage measured. Thus, the different sensor signals may vary a lot during normal operation, but certain variations may be allowed only in a specific state.

Obviously, those rather specific conditions for a proper operation are hardly to supervise just monitoring some thresholds as typically encountered in common combustion engine driven cars. Instead, learning a model of the battery parameters and state-related parameters like driver commands or motor current could lead to a relatively simple solution. Comparing model-based predictions and sensor measurements could allow a detection of many possible faults or handling errors, like for instance a battery heating defect, different kinds of battery defects, a (potentially unwanted) initialization of the battery storage mode, or a defect in the battery charging control. Using the proposed approach, the specific defect or its influence to the measured parameters not necessarily needs to be known. Of course only such problems can be detected that lead to deviations in one or multiple of the monitored parameters of the "‘normal"’ state previously learned. However, a defect that does not lead to measurable deviations in those parameters might be considered as negligible.

5 VEHICLE SETUPS FOR DATA COLLECTION AND TESTS

Two setup categories have been selected as suitable test and data collection platforms. The first one are standard electric vehicles (EV). The use of electric vehicles compared to combustion-engined vehicles is advantageous because of accessible interfaces on the actuation and the sensing side of the engine. Using standard EV in serial production supports a transferability of the results to later applications.

On the other hand, a more complex vehicle setup with additional sensor modalities might yield a more reliable safety detection. Therefore, in the second setup category a more complex vehicle with 23 DOFs was chosen.

5.1 Electrically Driven Common Vehicles

Even though todays modern cars already feature a large number of electrical sensors the data collected by those sensors is generally rather sparsely used. Especially many warning and error notifications are implemented in a very basic and mostly linear way.

For instance, if the oil level of a common combustion engine car reaches a certain – pre-defined – critical value, some warning light flashes up, signaling a certain urge to act to the user, e.g. to add some oil. This way of using the sensor data works fine to indicate a problem that had become present; but it remains unclear why and when it actually did arise. This poses the potential issue that the specific problem can be solved, but without knowing why it did arise it may as well occur again soon.

Additionally, there are certain states to be considered critical which do arise from a certain combination or succession of rather minor effects – none of which would have to exceed their individual fixed critical value and therefore wouldn't be detectable. Also, other effects like excessive wearing of certain components is detected only when its wear level eventually hits a critical value, ignoring the actual source of the excessive wearing itself.

The concept presented in this article supplies an approach to solve those difficulties. Using a definition of normal operation over the specification of certain fixed critical values enables to detect "unusual" or "deviating" states of operation as outlined in the examples stated before. Beyond those rather vehicle-focused applications the concept also allows to monitor the driver's behaviour, resp. driving performance, e.g. by contrasting the current state of operation by the driver against a certain "normal" state for detection of emergency or high stress states (e.g. extraordinarily strong braking, accelerating or steering behaviour) to which then appropriate reactions can be applied.

Duchrow et al. (Duchrow et al., 2012) presented a system for large-scale recording and analysis of EV fleet data. The data (like vehicle GPS position and battery state) is stored in a central data base. Such a large data base allows for additional fruitful uses like a definition of the normal/safe states needed for the concept based on the multiple data sources (e.g. vehicles normally operated, in terms of interindividual comparison), wear level monitoring (in terms of intra-vehicle runtime data comparison) or driver performance monitoring (in terms of intra-personal comparison) to just name some of the possible applications. The example data shown in section 4.2 is taken from this large-scale data base, too.

5.2 Multi-DOF Electric Vehicle

A more complex vehicle like the multi-DOF vehicle EO smart connecting car (EO scc, (Jahn et al., 2012)) not only allows for the implementation of additional sensors and the monitoring of extra data sources; its complexity also requires a more complex interface for its operation.

Figure 5: The electric vehicle EO scc (Jahn et al., 2012) which serves as a scientific test platform (© DFKI GmbH, Foto: PR Fotodesign).

It can be compared to the large amount of instruments and gauges in an aircraft which have to be monitored by the pilot. Whereas only some of those elements have to be permanently monitored, all of them can become important in certain situations and are therefore present in the pilots viewing area. It can become somewhat difficult to decide which element is of importance and has to be observed, which explains the rather extensive training that is needed to learn the correct operation of such a vehicle.

The approach presented in this article can help in such situations, as it can be used to monitor even the slightest deviations from the state of normal operation, which can then be used to emphasize the corresponding operation element.

For instance, instead of having a large variety of instruments and gauges to monitor and use at the same time (or, to be more specific: to decide from what to observe and use), the pilot or driver would only have to observe those elements that have been detected to be of special importance or showing a deviation from the normal state of operation, posing a great value of assistance in the operation of such rather complex vehicles.

Technically, the EO scc would be a suitable platform because of its way of implementation. Being more similar to a mobile robot than to an EV the control is implemented in software on embedded PC hardware. It uses the robot software framework "Rock" which is used for the tests described in section 4.1, too. Though such a system may yet not being suitable for usr in standard vehicles made in serial production; being a scientific test platform it allows even larger system changes in software or hardware with minimum additional effort.

6 CONCLUSION AND OUTLOOK

Presented was the concept of a holistic, model-based safety monitoring system for the application of intelligent vehicle control. Two main properties are a waiving of an explicit definition of unsafety and an integration of potentially multiple modalities (up to all available sensor and actuator modalities). Instead of defining an unsafe condition it is tried to learn the safe state (measured by one or muliple sensors). By this, in the application of the learned system any deviation from the "safe" (learned) state of a sufficent degree can be detected. This includes conditions which are not known at design or learning time.

The integration of multiple different modalities is supposed to a) allow to detect unsafe conditions which are hardly detectable on a single modality but which are pronounced on the whole set of measurements or to b) reject safe conditions which cause strong deviations on single modalities but none on other sensor readings.

As main components a learnable model, a prediction generation based on the model, and a monitoring of predictions (expectations) and measured sensor values are proposed. Besides the concept, a use-case aiming at potential electric vehicle defects or misoperations is presented.

After finishing tests of the proposed methods on a mobile robot platform, the same methods have to be tested with data collected on electric vehicles mentioned in this paper.

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