

Measuring Interaction-based Secondary Task Load: A Large-Scale Approach using Real-World Driving Data

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ABSTRACT

Center touchscreens are the main Human-Machine Interface (HMI) between the driver and the vehicle. They are becoming, larger, increasingly complex and replace functions that could previously be controlled using haptic interfaces. To ensure that touchscreen HMIs can be operated safely, they are subject to strict regulations and elaborate test protocols. Those methods and user trials require fully functional prototypes and are expensive and time-consuming. Therefore it is desirable to estimate the workload of specific interfaces or interaction sequences as early as possible in the development process. To address this problem, we envision a model-based approach that, based on the combination of user interactions and UI elements, can predict the secondary task load of the driver when interacting with the center screen. In this work, we present our current status, preliminary results, and our vision for a model-based system build upon large-scale natural driving data.

CCS CONCEPTS

• **Human-centered computing** → **Field studies; Pointing.**

KEYWORDS

in-vehicle information systems; driver behavior analysis; driver distraction

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1 INTRODUCTION

According to the National Highway Traffic Safety Administration (NHTSA) [15] 3,142 people were killed and 424,000 people were injured in crashes where drivers were distracted from the main driving task. Although the number of driver monitoring systems has increased steadily in recent years, a decrease in the number of accidents due to distracted driving can't be observed. Whereas the usage of smartphones during driving plays a major role, there

are concerns that the increase in complexity, capability, and size of touchscreen-based HMIs will additionally increase the driver's cognitive workload. To prevent automotive HMIs from being too distracting, they undergo expensive and time-consuming empirical testing before they can be integrated into production line vehicles. While such measures are essential and will remain necessary, early feedback on potentially distracting usage patterns can be valuable for UX experts to design systems that are safe to use. A system that can predict the secondary task load based on the anticipated UI interactions and their properties, such as the sequence in which they occur, can help UX experts to detect potentially distracting designs at an early stage and to develop appropriate alternatives. To enable such predictions, we envision a system leveraging driving and interaction data, automatically collected from a large amount of production line vehicles. Having access to such large-scale data makes it possible to generate insights that go beyond the detail of current, mostly qualitative or relatively small-scale naturalistic driving studies [5]. Additionally, as soon as a software update is deployed to the fleet, the changes that were made can directly be assessed. In this work, we investigate how the engagement of drivers with the touch-based HMI can be measured using driving parameters and UI interaction data.

2 RELATED WORK

Driver distraction measurement is a well-studied field of research that will remain relevant even in the approaching age of automated driving. Drivers will have to take over control of the vehicle in certain situations for a long time to come. For this reason, multiple approaches deal with driver distraction modeling and prediction. Many of such approaches are based on physiological data [1, 8, 19, 20] or eye-tracking data [7, 16, 17]. Whereas many of these approaches provide promising results and have proven their capability to effectively detect distracted driving, multiple factors prevent their large-scale usage. The main drawback of approaches based on physiological data is the fact that sensors need either to be attached to the body of the driver, or additional measurement units need to be installed in the car. This makes it nearly impossible to apply such methods outside of experimental environments or naturalistic driving studies. For approaches based on eye tracking, the costs of highly accurate eye-tracking systems are still a limiting factor for widespread deployment in production vehicles. Due to the highly sensitive nature of the data, most Original Equipment Manufacturers (OEMs) are reluctant to store video or gaze data. In contrast, methods based on driving data [4, 10, 12–14, 18] such as steering wheel angle, speed deviations, or vehicle accelerations, are more suitable for large-scale use cases since the data is already available in all modern cars and no additional instrumentation is

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Table 1: Processed Signals

| Variable | Unit | Description | Frequency |
|----------|----------|----------------------|-----------|
| v | km/h | Vehicle Speed | 5 Hz |
| θ | $^\circ$ | Steering Wheel Angle | 5 Hz |
| S | - | ADAS Status | On Change |
| UI | - | Touchscreen Event | On Change |

necessary. In 1999 Nakayama et al. [14] introduced the so-called Steering Entropy metric, showing clear correlations between an increase in driver workload and steering behavior. Additionally, Markkula and Engström [13] introduced the Steering Wheel Reversal Rate (SWRR) and compared it to other steering angle metrics concerning their sensitivity to the effect of secondary task workload on lateral control performance. Markkula and Engström found that the SWRR and the Steering Entropy are superior compared to other metrics. Whereas the original experiments and most of the studies that build upon the findings of Nakayama et al. and Markkula and Engström are based on data retrieved from simulator studies, a recent approach by Li et al., based on natural driving data, shows a clear correlation between driver distraction and high steering entropy. However only 16 drivers over 12 days contributed to the data collection and additional instrumentation was installed in the cars.

3 APPROACH

To model the effect specific user interactions or usage patterns on the touchscreen HMI have on secondary task load, a large amount of data is needed. This is due to the many UI elements and the even larger number of potential combinations in modern HMIs, as well as due to the diverse range of driving situations for which the effect might be different. Collecting this amount of data in naturalistic driving studies is time-consuming and expensive. Therefore, we want to base our approach on data collected from production vehicles. However, this results in a variety of other challenges. In contrast to laboratory studies, strict data protection regulations must be met, preventing the collection of personalized data. Additionally, due to the many different participants and the uncontrolled driving environment, the data quality is significantly different compared to simulator studies or controlled naturalistic driving studies. This makes a detailed data analysis and preprocessing necessary. In this work, we present our current state of research, namely the data collection and processing methods, the first preliminary results, and our research agenda.

3.1 Data Collection and Processing

The data used in this work is collected via a telematic framework that allows live Over-The-Air (OTA) data transfer from the car to the backend where the data is processed. The framework is available in the new generation of production vehicles and no additional instrumentation is needed. Detailed descriptions of the telematics architecture, processing framework, and data collection are provided by Ebel et al. [6].

First, interaction sequences are extracted. The event sequence data consists of timestamped events containing the name of the

interactive UI element that was triggered by the user and the type of gesture that was detected. We consider an interaction sequence to be a sequence of interactions where the time interval between two consecutive interactions is less than $t_{max} = 10 s$. In the second step, the interaction data is enriched with the driving data shown in Table 1. We only consider sequences in which the driver assistance systems were not active. For the remaining sequences, we also consider the driving data immediately preceding the first and immediately following the last interaction of a sequence. This is based on the assumption that the anticipated interaction with the HMI, before the actual gesture on the touchscreen is made, already influences the driving behavior. The same applies to the driving behavior shortly after the last interaction, as drivers tend to wait for visual confirmation and then reach back to the steering wheel. Considering the findings made by Large et al. [11], Green et al. [9], and Pettitt and Burnett [17], we choose a duration of $t_{buffer} = 2 s$. Applying the introduced preprocessing steps, 29,055 interaction sequences are extracted. To compare the driving behavior during *interaction sequences* with the driving behavior during *no-interaction sequences* we sampled the same amount of driving data snippets from sequences where no interactions were made. However, compared to a controlled experiment we define the no-interaction sequences such that during those periods no interactions were made with the in-vehicle HMI. We can't control for distractions happening outside of the head unit, for example, due to phone usage or passengers. To make a valid comparison between interaction sequences and no-interaction sequences we apply stratified sampling, such that the distribution in sequence length is equal in both groups.

After sequence extraction, aggregated statistics for each sequence as well as driver distraction metrics, namely SWRR (1, 2, and 5 degree according to Markkula and Engström [13]) and Steering Entropy (SE) (according to Nakayama et al. [14] with adjustments proposed by Boer et al. [2] to avoid extremely high entropies based on outliers) are calculated. Since no personalized data is available it is not possible to calculate a personalized α for the SE metric. We, therefore, averaged over all no-interaction sequences to obtain an average α .

3.2 Preliminary Results

Similar to Markkula and Engström [13], we compare the steering wheel metrics based on their standardized effect size d [3] and two different driving conditions. We differentiate between straight driving and curved driving since previous work [2, 13, 14] found that the SE and SWRR metrics are highly sensitive with regard to the road curvature.

As shown in Fig. 1 one can observe the difference in effect size between straight and curved driving, meaning that interaction and no-interaction sequences can be better separated for straight driving. The SWRR metrics are even more affected than the steering entropy. In general, the standardized effect sizes are smaller than reported by Markkula and Engström [13] (e.g. $d_{SE} = 0.34$ for the data in this work compared to $d_{SE} = 0.8$). Multiple reasons may cause this difference. The first and probably most important difference is the driving context in which the data was collected. Whereas, the dataset at hand comprises of multiple different driving scenarios, drivers, and interactions, the data used by Markkula and

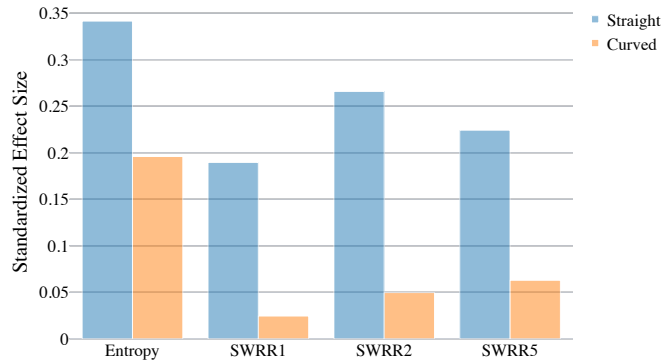


Figure 1: Standardized effect sizes for the steering wheel metrics and driving conditions (straight, curved)

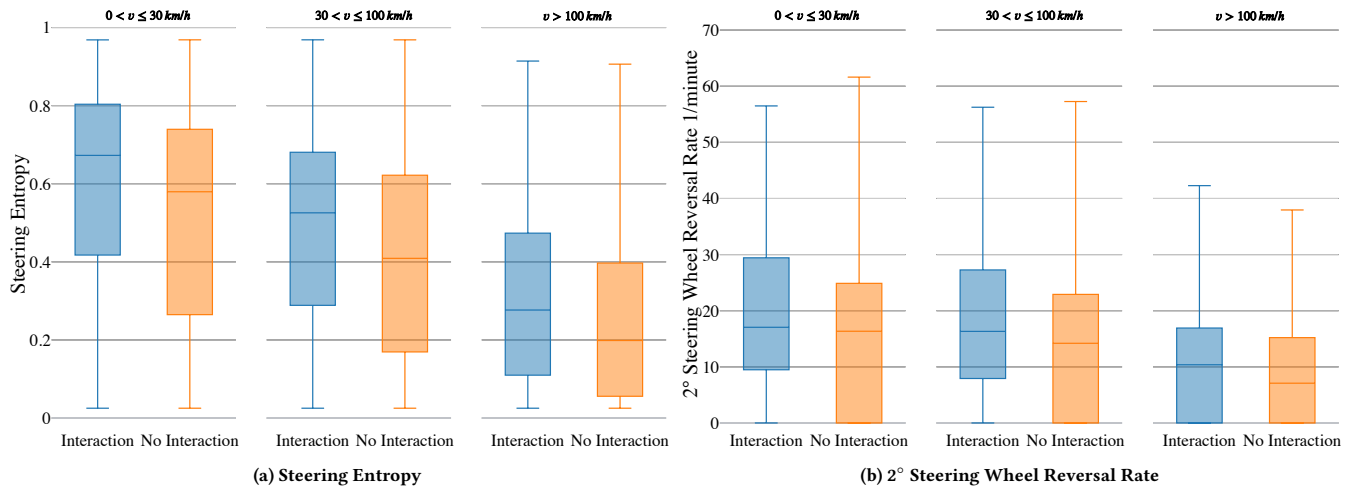


Figure 2: Steering Entropy and Steering Wheel Reversal Rate for straight driving sequences with HMI Interaction and without HMI interaction for different speed buckets.

Engström was collected in a field study, where 48 participants drove the same sequence on a motorway performing the same two tasks. Additionally, we did not yet tune the metrics to increase sensitivity.

In Fig. 2 a comparison between interaction and no-interaction sequences for straight driving is presented. We report the SE and the 2° SWRR since they have been found to be most sensitive. Even though the driving environment is highly uncontrolled and multiple confounding factors can influence the driving behavior, one can clearly observe the anticipated differences between interaction and no-interaction sequences for the SWRR and for the SE. One can see that the SE is larger for smaller vehicle speeds. Whereas the 2° and 5° SWRR measures show the same effect, this trend is not observable in the 1° SWRR (not displayed). A comparison of the 1° SWRR with the results from the field experiment conducted by Engström et al. [7] lead to similar results in the absolute values and

the difference between interaction sequences and no-interaction sequences.

3.3 Research Agenda

The preliminary results show that, even in the highly uncontrolled setting of real-world data, both metrics studied are suitable to measure secondary task load induced by HU touch interactions. In particular, the SE provides promising results in terms of sensitivity. Next, we plan to adjust the metrics to increase sensitivity. Then, building on the current state of work, we plan to evaluate the correlation between specific UI elements, interactions or interaction patterns, and driver distraction. Proving this correlation is an important step toward a predictive model of secondary task load. To then draw conclusions about the workload induced by specific interactions with certain UI elements, we plan to perform a feature importance analysis. First, we will use a machine learning-based

approach to predict steering entropy based on the proportion of different interactions (e.g. list tap or map drag) and additional meta-data like the number of interactions and interaction density. The insights generated via a feature importance analysis can then serve as a first feedback on interactions and interaction patterns that highly influence secondary task load. This information will then serve as a basis for further, more detailed, approaches.

4 DISCUSSION

In this work in progress, we present our planned approach to develop a model-based method, leveraging real-world data to predict secondary task load induced by interactions with a touchscreen HMI. The predictions should be based on the interactions and the respective UI elements used and can serve as an early-stage estimate of driver distraction far before the first experiments are conducted. Therefore, UX experts get early feedback on their designs which supports them to design non-distracting interfaces that increase road safety and additionally save costs since re-designs due to necessary changes discovered late studies can be avoided.

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