Estimating the Driver's Workload

Using Smartphone Data to Adapt In-vehicle Information Systems

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Abstract

Research Question: How can the driver's workload be estimated in order to adapt information and entertainment systems?
Approach: Smartphone sensor data, situational factors and basic user characteristics are collected. This data is tested whether it significantly influences workload and can be used to estimate it.
Method: Workload is measured with a smartphone-based representation of the NASA-TLX and the RSME during a user study with 20 participants on different road types.
Results: Driving situation, gender and driving frequency significantly influence workload. Using only this information and smartphone sensor data the driver's current workload can be estimated with 86% accuracy using a decision tree.

Keywords: Driver's workload, Workload estimation, In-vehicle information systems

In: F. Pehar/C. Schlögl/C. Wolff (Eds.). Re:inventing Information Science in the Networked Society. Proceedings of the 14th International Symposium on Information Science (ISI 2015), Zadar, Croatia, 19th–21st May 2015. Glückstadt: Verlag Werner Hülsbusch, pp. 543–548.

1 Motivation

Many in-vehicle information systems provide assistance or entertainment to the driver but still can be a source of distraction and cognitive load since they require the user's attention. Consequently, it would be advantageous to know the driver's mental state in order to avoid dangerous situations. For instance, a phone call could be blocked for a short period of time if the driver experiences a cognitively demanding situation. Driving is a particularly difficult setting for human computer interaction because the operator is supposed to master the so-called primary driving task, i.e. handling of the car (Michon 1986), before he or she can use any in-vehicle information system.

In this paper a study is presented that examines which factors significantly influence the driver's experience during the primary driving task. Furthermore, these factors and smartphone sensor data are used to estimate the driver's workload with different data mining techniques. Details of this work are published in Ohm and Ludwig (2013). In the remainder of this paper the concept of workload is briefly introduced followed by a description of the conducted study including the results. Finally, the findings are summed up.

2 Workload

Several definitions of workload exist which can be summed up as follows (see e.g.: Cain 2007, deWaard 1996, Hart & Staveland 1988): an operator has to fulfill a task under given situational circumstances which demands information-processing capabilities. Therefore, the task causes cognitive load. Workload is the required capability to accomplish the task satisfactorily. Meanwhile, the operator has a subjective experience which results from situational factors (e.g.: driving context), the requirements of the task and his or her characteristics (e.g., age).

Workload can be additionally sub-divided into different states. Oron-Gilad et al. 2008 distinguish three: if the requirements of the task exceed the skills of the user, he or she has to endure an overload experience. Contrary to this is the Underload state, which can be understood as a feeling of boredom or distraction. Both states should be avoided. Thus, if the factors are in balance, the driver is in an Optimal workload state. A more detailed but very similar categorization can be found e.g. in deWaard (1996).

Various available tools ranging from biosensors to user self-reports can be used to measure workload (see for an overview: deWaard 1996). For the study presented in this paper an adaptation of the Rating Scale Mental Effort (RSME) (Zijstra & Van Doorn 1985) was used. In the RSME the test person is asked to indicate how much effort it took to fulfill the task. Several statements like "rather much effort" are located along the scale, which are supposed to clarify the level of current effort. Furthermore, one of the most established (Cain 2007) multidimensional methods in this context was used: the NASA Task Load Index (NASA-TLX) which takes factors like the mental and physical demand as well as the subjectively experienced performance of the user into account (Hart & Staveland 1988).

3 Study

The following hypotheses (based on e.g.: Schweitzer & Green 2007, Oron-Gilad et al. 2008) were tested for validity in order to identify situational factors and user characteristics which significantly influence the driver's workload:

- H_1: Workload during the driving situations "freeway", "rural road" and "city" differs.
- H_2: Women and men experience different workload while driving.
- H_3: Workload levels differ considering the user's driving frequency.

Additionally, smartphone sensor data was collected for data mining.

3.1 Participants and test route

Eight female and twelve male students participated in the study with a mean age of 24.9 years (SD = 2.1) and a mean driving experience of 6.9 years (SD = 2.4). The entire test group consisted of young and rather inexperienced drivers. None of the participants drove with the test car before. The test route consisted of three sections (freeway, rural road and city). Each part could be accomplished in about 15 minutes and was five to twelve km long.

3.2 Measurements

The workload level after accomplishing every route section was measured using a smartphone-based representation of the NASA-TLX (fig. 1 middle and right). In addition, a tool based on a simplified version of the RSME was implemented so that users could rate their current workload during the driving process (fig. 1 left). The design of the tool is a result of a preliminary usability test with ten participants and four prototypes. During the test, participants were asked to indicate their workload level every time it had changed using the smartphone that was adjusted to the front screen. Additionally, this self-report was assigned to sensor data, e.g. the lateral and longitudinal acceleration as well as speed.

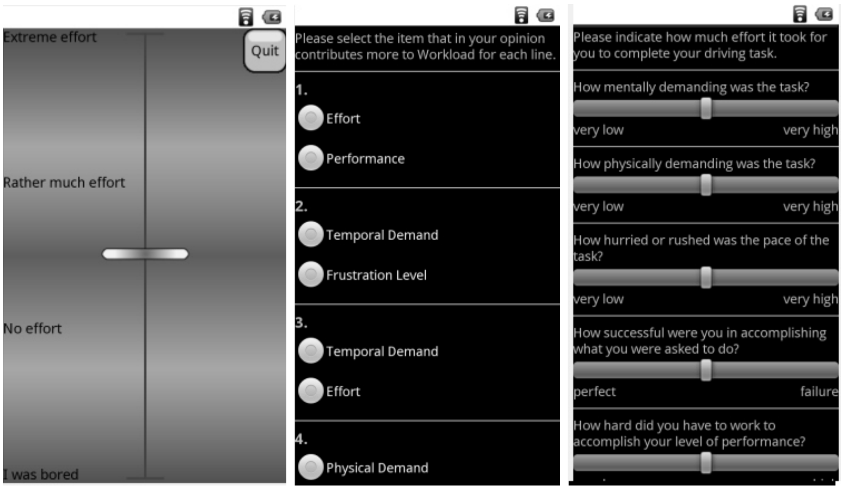

Figure 8. Screenshots of the workload measurement application

3.3 Results

The hypotheses were tested with the results of the NASA-TLX. First of all, normality was ensured with a Kolmogorov-Smirnov test ($p < 0.05$) and additionally by analyzing the histograms.

H_1 could be confirmed with a single factor variance analysis with repeated measurement ($p = 0.009$). The Bonferroni post-hoc test showed that workload levels are significantly higher for “freeway” ($p = 0.039$) and “city” ($p = 0.013$) compared to the “rural road” situation.

The Null-hypotheses of H_2 and H_3 could be rejected using a t-test ($p = 0.024$ and $p = 0.037$). Women experience slightly higher workload levels than men and participants who drive rarely endure more cognitive load than those who drive on a regular basis.

According to these findings, driving situation, gender and driving frequency were taken into account for the workload estimation in addition to the smartphone sensor data. Workload was categorized in the three states "Underload", "Optimal" and "Overload".

Different classification algorithms were taken into account using an 80/20 split of the sample data (see table 1). The results show that the decision tree performs significantly better than the other techniques ($p < 0.05$) and that the current cognitive load can be estimated with an accuracy of about 86%. Moreover, the ROC-value of the decision tree method exceeds 0.9 so that a good diagnostic accurateness can be assumed.

Table 1. Estimation accuracy in %

Decision Tree (C4.5)	Sequential Minimal Optimization (SMO)	AdaBoost	Naive Bayes	Neural Network
85.70	63.30	62.30	63.92	70.51

4 Conclusion and outlook

All in all, there are many factors which influence the driver's workload since the driving situation and the characteristics of the user are very multifaceted. However, the study presented in this paper shows that it is possible to estimate the driver's workload reaching a relatively high (compared to e.g.: Zhang et al. 2008 with 65%) prediction accuracy of 86% with smartphone data and very few user characteristics. Consequently, it would be advantageeous to shortly collect user data, i.e. gender and driving frequency. Furthermore, predictions could be improved by using information of the navigation system like the current road type.

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