Abstract

Traffic accidents are a major social issue, and driver assistance systems (DAS) are an effective means of reducing them. In particular, DAS that provide support tailored to diverse drivers with differing accident risks and preferences have the potential to significantly enhance safety and driving comfort. The ultimate goal of this research is to realize a personalized DAS that adapts to individual drivers, reduces accident risk, and promotes comfortable driving. Achieving such a system requires a deep understanding of drivers and the selection of effective assistance strategies based on this understanding. In this context, stable driver characteristics, such as driving style, cognitive ability, workload sensitivity, and personality, represent fundamental, DAS-independent properties that can serve as a shared basis for personalization across multiple assistance functions. However, it remains unclear whether such driver characteristics can be reliably estimated from naturalistic driving data, and which characteristics are most effective for improving the performance and acceptance of personalized DAS. This thesis addresses these challenges by investigating methods for estimating stable driver characteristics from driving data and exploring their application to the personalization of DAS.

First, this thesis estimates driver characteristics from naturalistic on-road driving data collected along a fixed driving route. Psychological driver characteristics, including cognitive function, psychological driving style, and workload sensitivity, were estimated by explicitly considering road types and multiple temporal scales of driving behavior. The results demonstrate that several cognitive function measures, particularly the Trail Making Test (TMT (B)) and Useful Field of View (UFOV), can be estimated with relatively high accuracy from driving data collected under controlled route conditions (Pearson's correlation coefficients of $r = 0.57$ and 0.70, respectively).

Next, this thesis extends the estimation framework to driving data collected from different routes in order to examine the robustness of driver characteristic estimation under varying driving environments. By focusing on driving scenarios that commonly appear across routes, the results show that cognitive function can still be estimated with moderate accuracy even when route conditions differ (Pearson's correlation coefficients of $r = 0.34$ and 0.48). Although estimation performance decreased compared to the fixed-route setting, the findings indicate that cognitive function represents a driver characteristic that can be robustly inferred from driving data across diverse driving routes.

While the first two studies focus on estimating driver characteristics from driving data, the third study examines whether personalized driving assistance based on driver characteristics is effective. The third study particularly focuses on driving support for speeding and sudden acceleration and deceleration, which represent high-risk driving behaviors and can be reliably measured from driving data. The results show that the effectiveness of such support differs depending on individual driver characteristics. In particular, drivers with high hesitation for driving or low confidence in driving skill exhibited limited behavioral improvements in response to speeding warnings. These findings indicate that speeding-related driving support should be adapted according to driver characteristics.

Fourth, this thesis investigates which driver characteristics are most effective for improving the performance and acceptance of personalized assistance at stop sign intersections, where accident risk is particularly high among older drivers. By comparing multiple assistance strategies that differed in both the amount and content of information provided, it was shown that drivers' responses varied systematically according to cognitive function, personality traits, driving style, and workload sensitivity. Drivers with reduced cognitive function benefited from instructive support, whereas drivers with high neuroticism or high hesitation for driving were negatively affected by information-rich assistance. These results demonstrate that the effectiveness of intersection-related driving support strongly depends on individual driver characteristics.

On the basis of these findings, this thesis provides a unified discussion on personalized DAS. Stable, DAS-independent driver characteristics, especially cognitive function and personality traits, were shown to be influential in determining the effectiveness of driving support and estimable from naturalistic driving data. These properties make them promising foundations for consistent personalization across multiple assistance functions. At the same time, the results of the estimation of driver characteristics highlight that not all relevant driver characteristics can be estimated with sufficient accuracy. For example, in a binary classification setting, confidence in driving skill and hesitation toward driving achieved F1 scores of 0.41 and 0.64, respectively, indicating important challenges for future research.

These results will lead to the development of techniques for understanding drivers on the basis of driving data from psychological and cognitive perspectives, and provide insights into how such techniques can be applied to the design of DAS. Then, the proposed approach enables implicit personalization without imposing additional burdens on drivers, while maintaining interpretability of the personalization process, making it suitable for real-world deployment.

Keywords: Driver Assistance Systems; Driving Behavior; Personalization; Machine Learning; Human-Computer Interaction