

Estimation of Driver Characteristics for Personalization of Driver Assistance Systems

Ryusei Kimura ¹⁾ Shogo Okada ¹⁾ Takahiro Tanaka ²⁾ Shuhei Manabe ³⁾

*1) Japan Advanced Institute of Science and Technology
1-1 Asahidai, Nomi, Ishikawa 923-1292, Japan (E-mail: s2110059@jaist.ac.jp)*

*2) Nagoya University
1 Furo-cho, Chikusa-ku, Nagoya, 464-8601, Japan*

*3) TOYOTA MOTOR CORPORATION
1 Toyota-Cho, Toyota City, Aichi Prefecture 471-8571, Japan*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Research Ethics Committee of the TOYOTA MOTOR CORPORATION.

KEY WORDS: Driving assistance system, Driver characteristics, Human engineering (C2)

Today, driving assistance systems are helpful tools to prevent traffic accidents and improve the driving experience. Most existing systems are made for average drivers. However, the demand or acceptance of systems depends on drives. Thus, the personalization of driving assistance systems improves safety and comfort. In particular, personalization based on driver characteristics such as personality and cognitive traits is important to meet the expectation of each driver. To realize such systems, we need to acquire driver characteristics. Prediction driver characteristics automatically from driving data is an effective way to acquire these driver characteristics without burdening the driver. In this paper, we aim to predict driver characteristics from driving data (such as acceleration, brake pressure, and steering angle) for the personalization of driving assistance systems. Especially, we focus on the situation where drivers drive different routes while existing studies that estimate driver characteristics from driving data experimented under the same route or condition. We develop the machine learning models to predict scores of aptitude tests of the National Agency for Automotive Safety & Victims' Aid (NASVA).

The dataset we use is presented from TOYOTA MOTOR CORPORATION and includes 1057 driving data obtained from 57 drivers. Driving data is composed of time series data of 119 sensors such as the speed, acceleration, brake pressure, steering angle, gaze position, and so on. We use 19 out of 119 sensors to capture driving behavior. The dataset includes the results of NASVA aptitude tests. The tests measure personality, safe driving attitude, cognitive and processing functions, and visual functions from both psychological and physiological aspects. We predict the results of these tests from driving signal data.

To estimate driver characteristics from driving data, where drivers drive different routes, we focus on several driving scenes, namely, intersections, lane changes, and continuous curves. We hypothesize that the differences in driver characteristics tend to be expressed in these scenes and are effective to estimate driver characteristics on different routes. These scenes often appear in driving, so we can acquire scene data easily. First, we segmented driving data into the intersection, lane change, and continuous curve. Moreover, intersection Then, statistics (mean, median, standard deviation, maximum, minimum, skewness, kurtosis) are extracted from each scene. We use these statistics as features for machine learning models. We use lasso regression, ridge regression, and random forest as regression models. The Pearson correlation coefficient (r) between predicted values and labels is used as a metric of the accuracy of the prediction model. Leave-One-Person-Out cross-validation is used to measure the accuracy of the prediction model.

Table 1 shows the results of the prediction that is the highest accuracy for each item. Lasso, Ridge, and RF represent lasso regression, ridge regression, and random forest, respectively. The item that achieved the highest r was thoughtfulness, with $r = 0.735$ for ridge regression for lane change (left). The highest r for emotional stability and decision/timing action are 0.041 and 0.149, respectively, which were particularly low compared to the other items. The highest r for other items exceeded 0.3 which implies a weak correlation. These results indicate that most items of NASVA aptitude tests can be estimated from driving data, especially, short driving scenes.

We also analyze effective features and interpret the relationship between driving behavior and driver characteristics. Using scene data makes it easier to interpret the prediction results and to capture the relationship between driving behavior and driver characteristics.

Table1 Prediction accuracy (r), driving scene, and regression model with the highest r for each item.

Item	r	Scene	Model
Emotional stability	0.041	Intersection	Ridge
Cooperativity	0.529	Curve (right)	RF
Generosity	0.599	Curve (right)	Ridge
Favor for others	0.374	Intersection (right)	Lasso
Safe driving attitude	0.485	Curve (right)	Ridge
Danger sensitivity	0.502	Curve (right)	Ridge
Attentiveness distribution	0.370	Curve (right)	Lasso
Performance accuracy	0.315	Intersection (left)	Ridge
Decision/timing action	0.149	Intersection (left)	Ridge
Thoughtfulness	0.735	Lane change (left)	Ridge
Dynamic visual acuity	0.541	Lane change (left)	Lasso
Eye movement	0.364	Lane change	Ridge