2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) | 979-8-3503-2447-1/23/$31.00 ©2023 IEEE | DOI: 10.1109/EMBC40787.2023.10341113

Driver's Cognitive Function Estimation Using Daily Driving Data

Ryusei Kimura[1], Takahiro Tanaka[2] and Shogo Okada[1]

***Abstract*— Driving assistance systems that support drivers by adapting to driver characteristics can provide appropriate feedback and prevent traffic accidents. Cognitive function is helpful information for such systems to assist older drivers, and automatic estimation of drivers' cognitive function enables systems to utilize this information without being burdensome to these drivers. Therefore, this study aims to estimate drivers' cognitive function from daily driving data. We focus on modeling the scores of Trail Making Test (A) and (B) as measures of cognitive function, which indicate general cognitive ability. The main challenge is learning the generalized mapping function to the cognitive status from driving behavioral features extracted from the different driving routes of each driver. To address this problem, the proposed method focuses on particular driving scenarios in which differences in cognitive function can be observed. We evaluate the performance of the proposed model and the effectiveness of driving scenario information. Experimental results show that the results of Trail Making Tests (A) and (B) can be estimated with Spearman rank correlation coefficients of $r = 0.34$ and 0.48, respectively. In addition, the proposed method makes it easier to analyze the relationships between driving behaviors and cognitive function by comparing driving behaviors (e.g., steering angle velocity) in specific driving scenarios (e.g., intersections).**

I. Introduction

Automobiles are essential tools for supporting the lives of many people, but they may present problems for older drivers. Older drivers are more prone to traffic accidents due to significant impairments in cognitive function [1]; nevertheless, there are many older people who do not wish to be restricted from driving. Driving restriction is an effective means to avoid accidents caused by older drivers, but it also causes considerable inconvenience.

To address this problem, driving assistance systems are one realistic solution to reduce accidents caused by older drivers without imposing driving restrictions. Also, autonomous driving may be helpful to prevent accidents, but it will be many years before all drivers around the world use autonomous driving vehicles. While driving assistance systems that are tailored toward older drivers have the potential to reduce traffic accidents [2], most existing systems are designed for average drivers [3] and cannot meet the demands of supporting older drivers suffering cognitive decline.

*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 Toyota Motor Corporation (Approval No. 2020UD0046).

[1]R. Kimura and S. Okada are with the School of Computer Science, Japan Advanced Institute of Science and Technology, Nomi, Ishikawa 923-1292, Japan {ryusei_kimura, okada-s}@jaist.ac.jp

[2]T. Tanaka is with the Institutes of Innovation for Future Society, Nagoya University, Furo-cho, Chikusa-ku, Nagoya, Aichi, 464-8601, Japan tanaka@coi.nagoya-u.ac.jp

Driving assistance systems that are adapted to drivers with cognitive decline are expected to assist them in situations where they have difficulty driving or where the risk of accidents is high.

In this work, as a first step toward implementing such adaptive assistance systems for older drivers, we aim to estimate the cognitive function of drivers from daily driving data using machine learning models. Cognitive function can be measured by several neuropsychology tests. We use the results from the Trail Making Tests (TMT) [4], well-validated neuropsychology tests, as measures of cognitive function. Automatic estimation of cognitive function is a fundamental technology for driving assistance systems that can adapt to the cognitive function of the driver. Such estimation can provide systems with information about the driver's cognitive function and capture cognitive decline without requiring burdensome cognitive tests.

However, this estimation task is difficult, and there are several related challenges. First, there are no established methods for estimating cognitive function based on driving behavior on different routes since no study has yet addressed this problem. Second, a vast amount of driving data can be collected from daily driving, and it is not clear which of these data best represent distinctive driving behaviors that are useful for estimation. Since a cognitive function is invariant for a short time, we can obtain only one cognitive function label data toward a vast amount of driving data. Therefore, it is important to select distinctive parts of driving data to estimate drivers' cognitive function accurately.

Although there have been several studies on the estimation of driving style from driving data [3], few researchers have addressed the estimation of drivers' cognitive function. Wallace et al. [5] predicted drivers with dementia, and the subjects drove along the same routes within simulation systems. Thus, the method proposed in [5] cannot be directly applied for the estimation of drivers' cognitive function from daily driving, as drivers travel along different routes. Accordingly, we collected a dataset from drivers traveling along different routes, and this study proposes a method of estimating cognitive function in such a situation. The dataset includes signals from various in-vehicle sensors, such as speed, braking, steering angle, and gaze position. Using these time-series sensor data, we estimate drivers' cognitive function.

We hypothesize that it is possible to estimate cognitive function by focusing on particular driving scenarios that are common across different routes. Since older drivers with low cognitive function are especially prone to accidents at intersections [6] and during lane changes [7], we hypothesize that

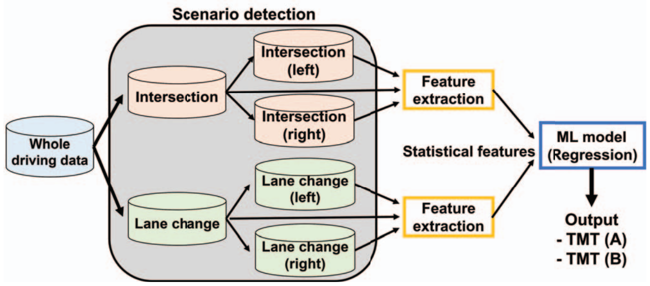

Fig. 1. Overview of the proposed method. First, whole driving data is segmented into some driving scenarios, and then features are extracted from each scenario data. Finally, a cognitive function is estimated by machine learning models.

differences in cognitive function may be relatively strongly expressed in driving behaviors found in these driving scenarios. Based on this hypothesis, we segment the driving data based on such driving scenarios and perform cognitive function estimation for each segmented driving scenario. This segmentation helps us analyze the relationships between cognitive function and driving behaviors.

II. Method

The statistics of overall driving data provide simple information about driving behaviors, but daily driving data include a wide range of driving behaviors that occur in diverse situations. Such simple statistical features lose detailed information that is important for driver characteristic estimation. Consequently, it is difficult to capture the intuitive relationship between driving behavior and cognitive function using such features. Instead, in this paper, we focus on particular driving scenarios, namely, intersections and lane changes. The overview of our proposed method is shown in Figure 1.

A. Dataset

In this paper, we use a dataset shared by Toyota Motor Corporation for our research purpose. The dataset includes 412 driving sessions obtained from 35 professional drivers driving on public roads in Japan. Note that in Japan, drivers drive on the left side of the road. The total time of driving data is approximately 7839 hours, and the average driving time for each driver is approximately 224 hours. The driving data consist of time-series signals obtained from 119 in-vehicle sensors. We use 19 of these sensors, as listed in Table I, and extract features for cognitive function estimation. Information on these sensors is related to cognitive function, driving skill, and driving style, and several studies have used them to predict driver characteristics [3]. Vehicle movements are reflected in sensors such as speed and steering angle, and driver behaviors such as gaze position and face angle are captured directly by a camera. Each signal is sampled at 10 Hz.

The dataset also includes the results of cognitive function tests. The Trail Making Test (TMT) [4] is used as a measure of cognitive function in this study. The drivers took two types of TMTs, namely, TMT (A) ($M = 35.0,\ std = 11.9$) and

TABLE I

In-vehicle sensors used for the estimation.

	Sensor
1	Stop lamp state
2	Brake pressure
3	Brake pressure velocity
4	Accelerator position
5	Speed
6	Forward acceleration
7	Forward jerk
8	Steering angle
9	Steering angular velocity
10	Turn lamp state (right)
11	Turn lamp state (left)
12	Yaw angle
13	Yaw rate
14	Fuel consumption
15	Gaze position (horizontal)
16	Gaze position (vertical)
17	Face angle (pitch)
18	Face angle (yaw)
19	Face angle (roll)

TMT (B) ($M = 67.1, std = 25.5$). In TMT (A), the subject connects numbers in sequence, and the time to completion is measured. In TMT (B), the subject connects numbers and letters in order. The TMT scores indicate test completion times, and higher scores on the TMT indicate lower cognitive function. The results of the TMT are correlated with the driving ability of older drivers and have been shown to be useful in measuring driving aptitude [8]. In this paper, we estimate the TMT results from daily driving data.

B. Driving scenario detection method

We use sensor data and rule-based methods to detect intersections and lane changes. Intersection events are classified into left turns at intersections and right turns at intersections, and lane changes are similarly classified into lane changes to the left and lane changes to the right.

For the detection of intersections, we first detect intervals that satisfy both a yaw rate of 3.0 deg/sec or higher and a change in yaw angle of 20 degrees or higher. Then, the detected intervals and the five seconds before and after each detected interval are extracted as intersection events. As exceptions, we exclude such events for which the change in yaw angle is smaller than 60 degrees and the minimum speed is 60 km/h or higher. Furthermore, the steering angle is used to classify the intersection events into left turns and right turns at intersections.

For the detection of lane changes, we consider the intervals that are five seconds before and after a time when the absolute value of the yaw rate exceeds 0.8 deg/sec to be lane change events. As exceptions, we exclude such events for which the average speed is less than 20 km/h or the turn lamp does not light. Similar to the intersection events, based on steering angle information, the intervals corresponding to lane changes are classified as lane changes to the left and lane changes to the right.

C. Machine learning models and feature extraction

We use the lasso regression, ridge regression, random forest, and long short-term memory (LSTM) models for estimation. The lasso regression, ridge regression, and random forest models use statistical features, while the LSTM model uses time-series signals of sensors.

With respect to statistical features, we extract features from each of the six scenarios detected in Section II-B separately (intersection, intersection (left), intersection (right), lane change, lane change (left), and lane change (right)). For each scenario, the extracted intervals are concatenated, and then the statistics are calculated from concatenated signals. Finally, one feature sample is obtained per driver. The statistical features considered are the mean, median, standard deviation, maximum, minimum, skewness, and kurtosis of the sensor values (Table I). Finally, 133 (19 sensors $\times$ six statistics) features are extracted and standardized for each scenario.

For time-series signal features, we resample the raw time-series signals of the sensors in Table I at 1 Hz, and they are input to the LSTM. To align the lengths of all time series signals, the first part of the time-series data was filled with zeros.

D. Experimental settings

For all models, the root mean square error (RMSE) is used as a measure of accuracy. Leave-one-out cross-validation is used to evaluate the accuracy of the models. We remove drivers whose TMT scores fall outside the range of $\mu \pm 2\sigma$ (where μ is the mean and σ is the standard deviation of the scores). The hyperparameters of the lasso regression, ridge regression, and random forest models are obtained through a grid search. Only features with a correlation of 0.1 or greater with the training labels are used for model training to avoid overfitting. The LSTM architecture is composed of one hidden layer with 20 units. The mean squared error (MSE) loss is used as the loss function. The number of epochs is 100, and optimization is performed with the ADAM optimizer. The initial learning rate is 0.1, and a learning rate of 0.05 is used after 30 epochs.

III. Results

To assess the effectiveness of a proposed method focusing on particular driving scenarios, we evaluate the regression accuracy of the proposed model. We compare the accuracy of the proposed model against the accuracy of a model using features extracted from all driving data as a whole. Since the size of all driving data is too large to train an LSTM model, LSTM experiments are not conducted with all driving data.

Table III shows the estimation accuracy. The bold values indicate the highest accuracy among the estimates for each cognitive function test. The TMT (A) score is estimated with the highest accuracy (lowest error) based on the lane change scenario by the random forest model, with an RMSE value of 10.27. The TMT (B) score is estimated with the highest accuracy (lowest error) based on the lane change (right) scenario by the random forest model, with an RMSE value of 21.55. Also, the RMSE value of the ridge regression based on the intersection (left) scenario is low, with an RMSE value of 21.79. The model using features extracted from all driving data does not achieve the highest accuracy. These results indicate that focusing on particular driving scenarios across different routes helps improve the estimation accuracy and enables the estimation of cognitive functions using daily driving data. Additionally, the accuracies of the LSTM model do not high.

TABLE II
THE REGRESSION ACCURACY FOR TMT (A) AND TMT (B).

Driving scene	Model	TMT (A)	TMT (B)
Intersection	lasso	19.74	48.38
	ridge	19.4	43.88
	RF	12.31	25.58
	LSTM	13.671	28.36
Intersection (left)	lasso	18.41	24.69
	ridge	18.45	21.79
	RF	12.9	25.52
	LSTM	12.07	24.55
Intersection (right)	lasso	16.52	40.34
	ridge	14.6	39.92
	RF	11.09	25.07
	LSTM	11.23	22.84
Lane change	lasso	15.03	34.47
	ridge	14.16	36.55
	RF	**10.27**	25.27
	LSTM	13.82	25.98
Lane change (left)	lasso	14.76	35.21
	ridge	15.57	29.5
	RF	12.09	24.72
	LSTM	15.09	28.25
Lane change (right)	lasso	18.34	33.09
	ridge	17.75	29.71
	RF	11.9	**21.55**
	LSTM	12.03	23.03
All driving	lasso	18.52	36.78
	ridge	16.96	35.8
	RF	11.77	25.17

TABLE III
THE TOP TWO RESULTS WITH THE BEST RMSE VALUE FOR TMT (A) AND TMT (B).

Driving scenario	Model	TMT (A)		TMT (B)	
		r	RMSE	r	RMSE
Lane change (right)	RF	0	11.9	0.33	**21.55**
Intersection (left)	Ridge	0	18.45	**0.48***	21.79
Lane change	RF	**0.34***	**10.27**	0	25.27
Intersection (right)	RF	0.15	11.09	0	25.07

We summarize the top two results with the best RMSE value for TMT (A) and TMT (B) in Table III and calculate the Spearman rank correlation coefficients (r). Correlation coefficients with p-values smaller than 0.05 are marked with *, and correlation coefficient values less than 0 are reported as 0. The highest r values are 0.34 and 0.48 for TMT (A) and TMT (B), respectively. We confirm that the highest correlation coefficients have p-values below 0.05. The scenarios with the highest r and RMSE are the same for TMT (A), while they are different for TMT (B). Based on these results, we find that the driving scenarios from which the TMT (A) and TMT (B) scores can be successfully estimated are not the same.

TABLE IV

THREE MOST EFFECTIVE FEATURES FOR ESTIMATION OF TMT (B) SCORE BASED ON THE SCENARIO OF INTERSECTION (LEFT).

Feature	Mean coefficient value
Steering angle velocity (skewness)	215.01
Yaw rate (kurtosis)	193.88
Forward jerk (median)	−192.97

IV. DISCUSSION

To reveal the relationship between driving behaviors and cognitive function, we analyze the effective features for estimating the TMT (B) score, which is estimated with the highest r value in Section III. We regard the absolute values of the standardized regression coefficients of ridge regression based on the intersection (left) scenario as the contribution of each feature. The average of these coefficients for a feature among the learned models is treated as its importance.

The three most important features for the estimation of TMT (B) are shown in Table IV. Drivers with low cognitive function (a high TMT score) tend to have higher values for the features with positive coefficients, while drivers with high cognitive function (a low TMT score) tend to have higher values for the features with negative coefficients in the regression models.

The skewness of the distribution of the steering angle velocity at intersections is the most important feature, with a positive coefficient value. Since positive skewness of a distribution means that the right tail is longer, the results indicate that the steering angle velocity of drivers with a high TMT (B) score is less likely to be high. Figure 2 shows examples of the distribution of the steering angle velocity at intersections for a driver with a high TMT (B) score and a driver with a low TMT (B) score, and the skewness of these distributions are 0.13 and -0.21, respectively. Regarding the yaw rate, distributions of drivers with a high TMT (B) score tend to have high kurtosis. Drivers with low kurtosis often perform left turns at a large yaw rate because kurtosis is a measure of whether the data are heavy-tailed. In addition, the coefficient of the median of the forward jerk is negative. Based on these analyses, drivers with a high TMT (B) score and low cognitive function tend not to perform quick left turns. Miyauchi et al. [9] presented a similar analysis and found that elderly drivers tend to have a lower rate of speeding, sudden braking, and sudden handling.

In [10], it was shown that at intersections, older drivers with worse TMT results were associated with low performance of visual-motor coordination, which refers to how well visual perception and fine motor skills are coordinated. Therefore, it is possible that drivers with low cognitive function take longer to process information and tend not to perform quick left turns at intersections, where complicated processing is required. These analyses explained which features are important to estimate the TMT scores by visualizing the weight of the model, and the results show the importance of the method focusing on particular driving scenarios. They provide motivation to search for other distinctive driving scenarios where drivers are required complicated processing for estimation.

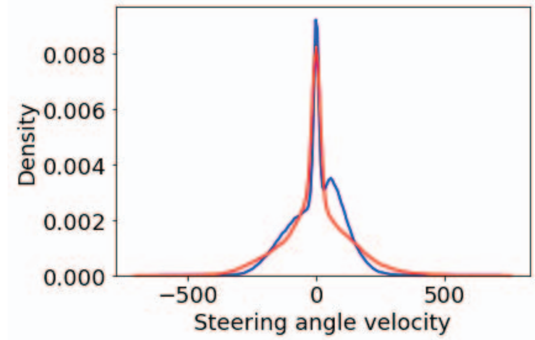

Fig. 2. Examples of the distribution of the steering angle velocity at intersections for a driver with a high TMT (B) score (red line) and a driver with a low TMT (B) score (blue line).

V. CONCLUSION

In this paper, we proposed a model for estimating a driver's cognitive function from daily driving data. We showed that focusing on particular driving scenarios that are common across different routes improves the estimation accuracy, and the highest estimation accuracies achieved for TMT (A) and TMT (B) scores were $r = 0.34$ and 0.48, respectively. Furthermore, the proposed model enables us to capture the relationships between driving behaviors and cognitive function. It was found that drivers with low cognitive function tend not to make quick left turns at intersections less often than those with high cognitive function. In this work, two driving scenarios, namely, intersections and lane changes were used for cognitive function estimation. Further studies are required to explore other driving scenarios and more accurate estimation methods.

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