Check for updates

Psychological Characteristics Estimation from On-Road Driving Data

Ryusei Kimura[1], Takahiro Tanaka[2], Yuki Yoshihara[2], Kazuhiro Fujikake[3], Hitoshi Kanamori[2], and Shogo Okada[1(✉)]

[1] Japan Advanced Institute of Science Technology, Nomi, Japan
{s2110059,okada-s}@jaist.ac.jp

[2] Institutes of Innovation for Future Society, Nagoya University, Nagoya, Japan
{tanaka,y-yuki,hitoshi_kanamori}@coi.nagoya-u.ac.jp

[3] School of Psychology, Chukyo University, Nagoya, Japan
fujikake@lets.chukyo-u.ac.jp

Abstract. Automobiles are essential to society, while they cause some problems. In particular, traffic accidents by older drivers are a serious problem. Driving assistance systems are promising solutions to this problem. However, it is not easy to develop acceptable and comfortable driving assistance systems for all drivers. To realize such systems, we need to consider the driver characteristics or personality of the drivers.

In this paper, we predict the psychological characteristics of older drivers from on-road driving data and propose a classification model. We posit that road types are important information for estimation and that important driving behaviors appear not only in whole driving but also in partial driving. Under these hypotheses, our feature extraction method segments time-series data using road types and further segments data into various duration sequences. Experimental results show that some items can be predicted with high accuracy and validate the efficacy of the segmentation. We use a dataset that includes time-series driving data, the Driving Style Questionnaire scores, and the Workload Sensitivity Questionnaire scores of 24 older drivers. Also, this study gives a new perspective to the prediction of individual characteristics.

Keywords: Driver characteristics · Driving style · Driving workload · Driving assistance systems · Social signal processing · Multimodal

1 Introduction

Automobiles are beneficial and indispensable to society, but they cause some problems. In particular, traffic accidents by older drivers are a serious problem. According to the report by the Centers for Disease Control and Prevention, approximately 8,000 older adults were killed in traffic crashes, and more than 250,000 were treated in emergency departments for crash injuries in 2019 [1]. Driving assistance systems are one of the solutions to this problem, but it is not easy to develop acceptable and comfortable driving assistance systems for

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2022
G. Meiselwitz (Ed.): HCII 2022, LNCS 13315, pp. 146–159, 2022.
https://doi.org/10.1007/978-3-031-05061-9_11

all drivers. Exiting systems are usually designed based on average driver characteristics [2] even though there are various types of drivers. Therefore, some people feel uncomfortable with feedback on driving and ignore systems. To realize acceptable and individualized driving assistance systems, we need to consider driver's characteristics. Thus, driver's characteristics recognition is an important task. Representative characteristics of drivers are driving style, and a lot of previous research has focused on driving style recognition from driving data. However, recognition of psychological aspects of driving style has not been focused on. Although sensitivity to driving workload is also one of the important characteristics of drivers, similar to the psychological driving style, psychological sensitivity to driving workload has not been focused on, and no study estimates it from driving data. Several studies showed the relationship between driving performance and personality [3,4], and stress [5,6].

Based on these results, we posit that psychological driving style and psychological sensitivity to driving workload can be estimated from driving data. Our goal is to estimate the psychological driving style and the psychological sensitivity to the driving workload of older drivers from on-road driving data. As metrics of them, we use Driving Style Questionnaire (DSQ) [7], and Workload Sensitivity Questionnaire [8], which are measured based on a self-report questionnaire. We use the dataset in [9], which includes time-series driving data and scores of DSQ and WSQ of older drivers.

This paper proposes a model for estimating psychological driving style and sensitivity to driving workload. We incorporate two hypotheses to our model that road types are important information for estimation and that important driving behaviors appear not only in whole driving but also in partial driving. Our model can consider different driving scenes and capture important driving behavior for estimation by segmenting time-series driving data. In addition to the estimation, we analyze road type-specific differences of effective sensors and the duration of important driving behaviors. These analyses give clues to further study on estimation of drivers' psychological characteristics.

In the area of social signal processing, psychological characteristics or personality traits are predicted from a great variety of data sources, for example, multi-party meetings [10], social media [11], speech [12], and game [13]. However, predicting psychological characteristics from driving data has not been shed light. This study gives a new data source and a new method to predict psychological characteristics to social signal processing.

The rest of this paper is organized as follows. In Sect. 2, we describe existing related studies. Then, Sect. 3 details the dataset used in our experiments. We explain the feature extraction method in Sect. 4. The experimental setting is presented in Sect. 5, and the experimental results are presented in Sect. 6. In Sect. 7, we discuss the results of the experiments. Finally, Sect. 8 concludes this paper.

2 Related Works

This study focuses on estimating drivers' psychological characteristics from driving data. No previous study has addressed this estimation, but several studies analyzed the relationship between driving and personality. We hypothesize that psychological characteristics can be estimated from driving data based on the previous study. This research is also related to driving assistance systems.

2.1 Relationship Between Driving and Personality

Some studies revealed that driving performance is related to personality. Adrian et al. [3] investigated the relationship between driving performance and personality traits among older drivers. It was reported that personality (extraversion) is negatively related to driving performance. In [14], aggressive driving, crashes, and moving violations are predicted by the driver's personality. Guo et al. [15] found that driver's personality traits affect accident involvement and risky driving behavior. Also, an association between driving stress and personality was indicated in [5].

2.2 Driver Assistance Systems

To date, various types of driver assistance systems have been proposed, and they are grouped into two broad categories: those that promote safe driving and those that improve fuel efficiency. There are various ways in which the driver assistance systems provide feedback. Stoichkov et al. [16] proposed a visual feedback system that lowers fuel consumption and the risk of traffic accidents. Fazeen et al. [17] proposed audio feedback systems using a smartphone for safety awareness. These feedback systems are easy to implement and cause less discomfort than other approaches but may be ignored by a driver and cannot always force them to acknowledge the feedback. Xu et al. [18] developed a system that stiffens the accelerator pedal according to the discrepancy between the actual vehicle speed and the desired vehicle speed. Although such systems feature enforcement against the drivers, some drivers may feel uncomfortable and disable them. Syed et al. [19] analyzed drivers' acceptance of the feedback systems. The automatic estimation of the driver's personality traits enables such assistance systems to support the individual driver adaptively.

3 Dataset

In this study, we use the dataset provided by the Institute of Innovation for Future Society of Nagoya University [9]. The dataset is collected from driving tests, and 24 older drivers participated. The participants drove a car equipped with various sensors including a GPS sensor in the driving tests. They drove two times each, but we used 38 driving data (23 drivers) because the seven driving data have large missing parts. Hence, there are drivers whose two driving data are used and one driving data is used. The driving tests were conducted on public roads around Nagoya city. In the tests, all participants departed from Nagoya University first, then drove on the arterial road, and then circumnavigated the residential area, finally, returning to Nagoya University. The total mileage and the total driving time are different for each participant. The driving duration ranged from 2245 s to 4762 s, with an average of 2885 s. The Mileage ranged from 10079 m to 14810 m, with an average of 12109 m. Figure 1 shows a car used in the tests. In addition to the driving tests, the drivers answered questions about driving style and workload.

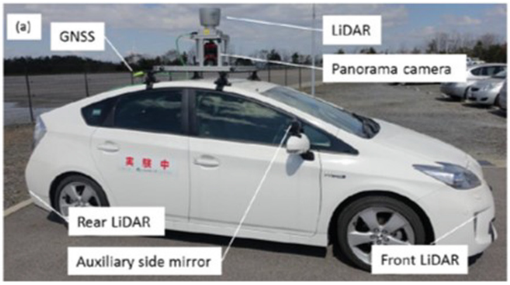

Fig. 1. The car used in driving test.

3.1 In-vehicle Sensor Data

The Participants drive public roads with cars which equip with 38 in-vehicle sensors. The driving data is obtained through Controller Area Network (CAN). We use 12 in-vehicle sensors which are detailed in Table 1 plus GPS sensor. The GPS sensor is only used for preprocessing of driving data. The cars did not equip with a jerk sensor. Hence, jerk values are calculated by the first-order difference of estimated acceleration. The example of the time-series data of steering angle is shown in Fig. 2.

3.2 Driving Style Questionnaire and Workload Sensitivity Questionnaire

Driving Style Questionnaire (DSQ) and Workload Sensitivity Questionnaire (WSQ), which are based on a self-report questionnaire are introduced by [7] [8] for characterizing drivers from a psychological aspect. In [8], the relevance between car following behavior and DSQ are validated. Table 2 and Table 3 detail the items of DSQ and WSQ. DSQ has eight items on a scale from 1 to 4, and WSQ has 10 items on a scale from 1 to 5. We classify drivers with high and low scores of DSQ and WSQ items.

Table 1. In-vehicle sensors.

	Sensor	Unit
1	Steering angle	deg
2	Electronic power steering (EPS) torque	Nm
3	Forward acceleration	m/s^2
4	Lateral acceleration	m/s^2
5	Yaw rate	deg/sec
6	Speed	km/h
7	Forward right wheel speed	km/h
8	Forward left wheel speed	km/h
9	Accelerator position	%
10	Brake pressure	MPa
11	Estimated acceleration	m/s^2
12	Fuel consumption	ml

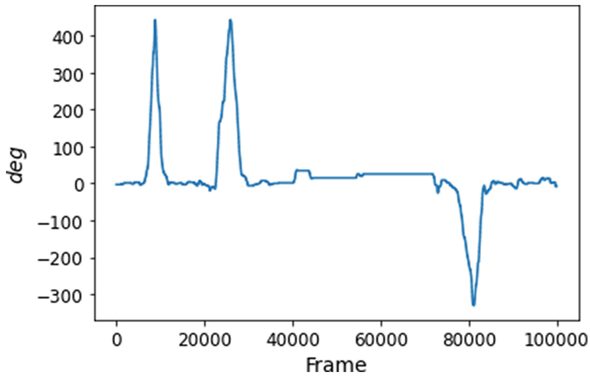

Fig. 2. The example of the time-series data of steering angle.

Table 2. Driving Style Questionnaire (DSQ).

	Item
1	Confidence in driving skill
2	Hesitation for driving
3	Impatience in driving
4	Methodical driving
5	Preparatory maneuvers at traffic signals
6	Importance of automobile for self-expression
7	Moodiness in driving
8	Anxiety about traffic accidents

Table 3. Workload Sensitivity Questionnaire (WSQ).

	Item
1	Understanding of traffic conditions
2	Understanding the road conditions
3	Interference with concentration
4	Decline in physical activity
5	Disturbance on the pace of driving
6	Physical pain
7	Path understanding and search
8	In-vehicle environment
9	Control operation
10	Driving posture

4 Feature Extraction

To classify drivers, we extract features from time-series sensor data listed in Table 1 plus a jerk. Our feature extraction method is based on two hypotheses. The first hypothesis is that driving behaviors that are related to drivers' psychological characteristics and workload are different among road types. Since driving behavior is strongly related to road type, several studies on driving style recognition from driving data used road type information [20,21]. Besides, mental workload in driving depends on road context [22] and visibility [23]. Based on this hypothesis, we segment time-series driving data into two road types, namely, arterial roads and intersections. Then, features are extracted from each road type. The driving data is segmented by the car's position obtained through the GPS sensor. We use four intersections where all drivers' data were recorded accurately. We treat these four intersections as the same road types, but features are extracted separately because the visibility and ease of driving are not equal. Figure 3 shows the driving route in the tests.

The second hypothesis is that differences in drivers' psychological characteristics appear not only in whole driving but also in partial driving. We further segment time-series driving data into many sequences with various durations because we have no a priori knowledge about when or where the important driving behaviors for predicting psychological characteristics appear. The time-series data of arterial roads are segmented so that the duration of each segment is equal and the average duration for each segment is [All, 60, 30, 15, 10, 5, 3]. "All" means no division, i.e., whole arterial road (with an average of 355 s). For intersections, since time-series data are too short, they were segmented into the first and second halves of each intersection. This segmentation capture both long-term and short-term driving behavior. Statistics (mean, median, variance, maximum, kurtosis, and skewness) are calculated from each sequence and used as input features of machine learning models. An overview of the model is shown in Fig. 4.

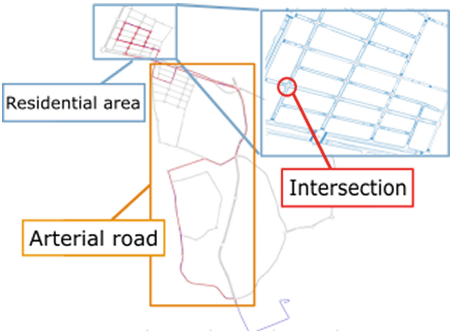

Fig. 3. Driving test route (red line). (Color figure online)

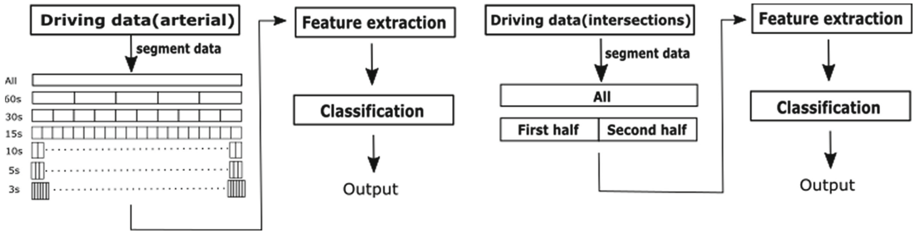

Fig. 4. Overview of the model. The left side shows an overview of the arterial road and the right side shows an overview of the intersections.

5 Experimental Setting

We classify drivers with high and low scores of DSQ and WSQ and evaluate the accuracy of the classification models. We use logistic regression with L2 regularization, linear support vector machine, random forest as classification models. Deep neural network models such as a 1-D CNN and LSTM are suitable for time-series data. However, we do not use them in the present study because the amount of data is too small to train prediction models. The regularization parameter values of the logistic regression and linear support vector machine are selected from [0.001, 0.01, 0.1, 1, 10, 100]. The maximum depth of the tree of the random forest is selected from [3,5,7,9,11]. These hyperparameters are tuned in the training set. As an evaluation criterion of classification models, we report an F1-score because a class imbalance occurs in some items. We use leave-one-person-out cross-validation to evaluate classification models. To avoid overfitting, we apply feature selection for each fold, and features that correlate with scores of each item with $|r| > 0.1$ are used. Scales of DSQ and WSQ are different; we split these scores based on the median value to create binary classification labels and then, conduct binary classification.

6 Results

To evaluate our models and the efficacy of two types of segmentation by road types and sequences of various duration, we compare three models, namely, (i) a model with both road type and various duration segmentation, (ii) a model only with road type segmentation, and (iii) a model without any segmentation. Model (i) and (ii) predict drivers' psychological characteristics separately on the arterial roads and at the intersections.

6.1 Comparison Between Various Duration Segmentation Models

First, we focus on the classification accuracies of the two models with various duration segmentation and compare them. Tables 4 and Table 5 respectively show the classification results of DSQ and WSQ. Columns 2 to 4 in Tables 4 and 5 show the accuracies of the models with two types of segmentation (i) and columns 5 to 7 show the accuracies of the models without various duration segmentation (ii). LR, SVM, and RF denote logistic regression, support vector machine, and random forest. The bold values indicate the highest accuracy among all models and road types for each item.

Concerning DSQ, the model (i) achieved the best accuracies in six items while the model (ii) achieved the best accuracies in four items. For all DSQ items, the best F1 scores were above 0.7. In particular, the best F1 scores of confidence in driving skill, impatience in driving, and anxiety about traffic accidents were 0.831, 0.825, and 0.848, respectively. These scores were comparably high and exceeded 0.8. Concerning WSQ, the model (i) achieved the best accuracies in five items, and the model (ii) achieved the best accuracies also in five items. In comparison with the result of DSQ, the accuracies for WSQ were low and only two items, control operation and driving posture had the best F1 scores above 0.7.

For both DSQ and WSQ, all best F1 scores were higher than 50%, random-assignment baseline. According to this result, our models worked well for estimating the driver's psychological aspect, but, for some items, the accuracy was not high, particularly WSQ items. The various duration segmentation improved the F1 scores of importance of automobile for self-expression (DSQ) and decline in physical activity (WSQ) by 0.143 and 0.104, respectively. However, in other items, segmentation resulted in slight improvement or degradation.

Table 4. Classification accuracy (F1-score) of the model with and without various duration segmentation for DSQ.

	With segmentation			Without segmentation		
DSQ	LR	SVM	RF	LR	SVM	RF
Arterial road						
Confidence in driving skill	0.754	0.754	**0.831**	**0.831**	0.56	0.774
Hesitation for driving	0.618	0.593	0.733	0.754	0.625	0.618
Impatience in driving	0.794	0.774	0.812	**0.825**	0.746	0.794
Methodical driving	0.702	0.712	**0.774**	0.714	0.615	0.724
Preparatory maneuvers at traffic signals	0.512	0.565	0.5	0.714	0.667	0.636
Importance of automobile for self-expression	0.566	0.593	0.69	0.538	0.553	0.56
Moodiness in driving	**0.759**	0.746	0.733	0.75	0.565	0.692
Anxiety about traffic accidents	**0.848**	0.831	**0.848**	0.813	0.75	0.787
Intersections						
Confidence in driving skill	0.733	0.618	0.812	0.754	0.727	0.812
Hesitation for driving	**0.755**	**0.755**	0.654	0.627	0.642	0.667
Impatience in driving	0.759	0.737	0.774	0.737	0.75	0.774
Methodical driving	0.69	0.468	0.691	0.643	0.56	0.69
Preparatory maneuvers at traffic signals	0.727	0.739	0.652	**0.766**	**0.766**	0.682
Importance of automobile for self-expression	**0.708**	**0.708**	0.655	0.553	0.565	0.542
Moodiness in driving	0.692	0.706	0.702	0.733	0.565	0.702
Anxiety about traffic accidents	0.774	0.787	0.831	0.831	0.82	**0.848**

6.2 Comparison with Road Type Segmentation Models

Second, we compare the results of the models with and without road type segmentation. Tables 6 and 7 respectively show the classification results of DSQ and WSQ of the model without any segmentation (iii). The bold values indicate the F1 scores that are higher than the best F1 scores of the models with road type segmentation (i) and (ii). For the model (iii), only anxiety about traffic accidents (DSQ) was predicted more accurately with the F1 score of 0.871, and the accuracies of other items were not more than the accuracies of the models (i) and (ii). Therefore, road type segmentation worked well to estimate drivers' psychological characteristics.

Table 5. Classification accuracy (F1-score) of the model with and without various duration segmentation for WSQ.

	With segmentation			Without segmentation		
WSQ	LR	SVM	RF	LR	SVM	RF
Arterial road						
Understanding of traffic conditions	0.625	0.625	**0.667**	0.51	0.324	0.654
Understanding road conditions	0.5	0.583	0.64	0.458	0.5	0.455
Interference with concentration	0.429	0.419	0.458	**0.679**	0.381	0.35
Decline in physical activity	0.429	0.368	0.439	0.417	0.429	0.381
Disturbance on driver's pace	0.526	0.571	**0.609**	0.538	0.537	0.455
Physical pain	0.333	0.409	0.458	0.531	0.537	0.35
Path understanding and search	0.372	0.341	0.103	0.41	0.462	0.25
In-vehicle environment	0.372	0.612	0.56	0.652	0.696	0.625
Control operation	0.605	0.571	0.462	0.41	0.389	0.474
Driving posture	0.69	0.577	0.746	**0.774**	0.531	0.69
Intersections						
Understanding of traffic conditions	0.565	0.545	0.52	0.565	0.5	0.52
Understanding road conditions	**0.667**	0.619	0.612	0.591	0.578	**0.667**
Interference with concentration	0.522	0.45	0.489	0.578	0.622	0.489
Decline in physical activity	**0.683**	0.6	0.667	0.571	0.537	0.579
Disturbance on driver's pace	0.524	0.585	0.545	0.571	0.512	0.571
Physical pain	0.5	0.476	0.5	0.533	**0.591**	0.488
Path understanding and search	0.564	0.632	0.5	0.649	**0.684**	0.667
In-vehicle environment	**0.698**	0.714	0.609	0.652	0.683	0.545
Control operation	0.619	0.488	0.619	0.558	0.537	**0.718**
Driving posture	0.511	0.533	0.593	0.667	0.612	0.577

Table 6. Classification accuracy of the model without road type segmentation for WSQ.

WSQ	LR	SVM	RF
Confidence in driving skill	0.831	0.618	0.754
Hesitation for driving	0.549	0.609	0.679
Impatience in driving	0.812	0.615	0.794
Methodical driving	0.667	0.68	0.655
Preparatory maneuvers at traffic signals	0.651	0.667	0.553
Importance of automobile for self-expression	0.636	0.651	0.667
Moodiness in driving	0.724	0.625	0.727
Anxiety about traffic accidents	**0.871**	**0.852**	**0.862**

Table 7. Classification accuracy of the model without road type segmentation for DSQ.

WSQ	LR	SVM	RF
Understanding of traffic conditions	0.566	0.591	0.553
Understanding road conditions	0.622	0.667	0.609
Interference with concentration	0.6	0.6	0.444
Decline in physical activity	0.455	0.564	0.308
Disturbance on driver's pace	0.364	0.476	0.476
Physical pain	0.542	0.45	0.263
Path understanding and search	0.381	0.55	0.486
In-vehicle environment	0.681	0.634	0.512
Control operation	0.378	0.524	0.579
Driving posture	0.774	0.653	0.69

7 Discussion

We investigated the contributions of features or sensors to classification, and then describe the effectiveness of two types of segmentation.

7.1 Contribution of Each Sensor

We analyze which sensors were effective for classification and reveal that the importance of features depended on road types. We focus on the results of the model with two types of segmentation and compare important sensors to classify confidence in driving skill between different road types. This item was predicted accurately in both road types. We regard the mean decrease in the impurity of random forest for each feature as the feature importance to the prediction. Then, they summed up to calculate the importance of each sensor. Table 8 shows the five most important sensors for the arterial roads and the intersections. The arterial roads and the intersections have common effective sensors, EPS torque and yaw rate. Sensors for acceleration are important for arterial roads, while sensors for speed are important for intersections. We confirm that important sensors depended on road types also in other items. These differences occurred due to the difference in driving behavior among road types. Thus, it is assumed that the classification models with road type segmentation can capture this difference and improve accuracy.

Table 8. The five most important sensors for classification.

	Arterial roads	Intersection
1	EPS torque	EPS torque
2	Yaw rate	Yaw rate
3	Forward acceleration	Forward left wheel speed
4	Lateral acceleration	Forward right wheel speed
5	Estimated acceleration	Speed

7.2 Contribution of the Segmentation

To verify the efficacy of various duration segmentation, We analyze which duration of segments worked well for classification. As in the previous subsection, we focus on the results of confidence in driving skill of the model with two types of segmentation. Feature importance is calculated in the same way as in the previous subsection and summed up the importance for each segment duration. Table 9 shows relative proportions of feature importance for each segment duration. We compare the feature importance with normalization by the number of segments or without normalization because the number of segments is different depending on the duration of segments.

Without normalization, the proportions of features of 3 s and 5 s were larger than that of other segment duration. With normalization, proportions of short duration segments became small, while proportions of long duration segments became large. This tendency was also seen in other items. This result indicates that short-duration driving behaviors have a lot of contributions for estimating drivers' psychological characteristics, but important features are only a part of them. This result demonstrates that important driving behaviors appear not in whole driving but in partial driving. Additionally, many features of short-duration segments are too localized and are not robust due to sensor noise.

Table 9. Relative proportion of importance of each segment duration.

Duration of segment	Unnormalized	Normalized
All	0.3%	11.0%
60 s	2.3%	12.9%
30 s	5.2%	14.7%
15 s	9.7%	15.2%
10 s	16.0%	17.1%
5 s	25.5%	14.5%
3 s	41.0%	14.6%

8 Conclusion

In this paper, we addressed a challenging task, estimating the psychological characteristics of drivers from on-road driving data. We presented a model for estimation and it could estimate with high accuracy. In particular, confidence in driving skill, impatience in driving, and anxiety about traffic accidents were accurately classified with F1 scores of 0.831, 0.825, and 0.848, respectively. In addition to this estimation, we revealed that important sensors depended on road types and that important driving behaviors had various duration. This study gives a baseline of estimation of psychological characteristics from driving data and benefit analysis.

References

1. Centers for Disease Control and Prevention. Older adult drivers (2021). https://www.cdc.gov/transportationsafety/older_adult_drivers/index.html. Accessed 11 Jan 2022
2. Martinez, C.M., Heucke, M., Wang, F.-Y., Gao, B., Cao, D.: Driving style recognition for intelligent vehicle control and advanced driver assistance: a survey. IEEE Trans. Intell. Transp. Syst. **19**(3), 666–676 (2017)
3. Adrian, J., Postal, V., Moessinger, M., Rascle, N., Charles, A.: Personality traits and executive functions related to on-road driving performance among older drivers. Accident Anal. Prevention **43**(5), 1652–1659 (2011)
4. Classen, S., Nichols, A.L., McPeek, R., Breiner, J.F.: Personality as a predictor of driving performance: an exploratory study. Transp. Res. Part F: Traffic Psychol. Behav. **14**(5), 381–389 (2011)
5. Matthews, G., Dorn, L., Glendon, A.I.: Personality correlates of driver stress. Personality Individ. Differ. **12**(6), 535–549 (1991)
6. Dorn, L., Matthews, G.: Two further studies of personality correlates of driver stress. Personality Individ. Differ. **13**(8), 949–951 (1992)
7. Ishibashi, M., Okuwa, M., Doi, S., Akamatsu, M.: Indices for characterizing driving style and their relevance to car following behavior. In: SICE Annual Conference 2007, pp. 1132–1137. IEEE (2007)
8. Ishibashi, M., Okuwa, M., Doi, S., Akamatsu, M.: Indices for workload sensitivity of driver and their relevance to route choice preferences. In: The Second International Symposium on Complex Medical Engineering, pp. 71–74, May 2008
9. Yoshihara, Y., Takeuchi, E., Ninomiya, Y.: Accurate analysis of expert and elderly driving at blind corners for proactive advanced driving assistance systems. In: Transportation Research Board 95th Annual Meeting, no. 16–1992 (2016)
10. Mana, N., et al.: Multimodal corpus of multi-party meetings for automatic social behavior analysis and personality traits detection. In: Proceedings of the 2007 Workshop on Tagging, Mining and Retrieval of Human Related Activity Information, pp. 9–14 (2007)
11. Philip, J., Shah, D., Nayak, S., Patel, S., Devashrayee, Y.: Machine learning for personality analysis based on big five model. In: Balas, V.E., Sharma, N., Chakrabarti, A. (eds.) Data Management, Analytics and Innovation. AISC, vol. 839, pp. 345–355. Springer, Singapore (2019). https://doi.org/10.1007/978-981-13-1274-8_27

12. Polzehl, T., Möller, S., Metze, F.: Automatically assessing personality from speech. In: 2010 IEEE Fourth International Conference on Semantic Computing, pp. 134–140. IEEE (2010)
13. Yaakub, C.Y., Sulaiman, N., Kim, C.W.: A study on personality identification using game based theory. In: 2010 2nd International Conference on Computer Technology and Development, pp. 732–734 (2010)
14. Dahlen, E.R., Edwards, B.D., Tubré, T., Zyphur, M.J., Warren, C.R.: Taking a look behind the wheel: an investigation into the personality predictors of aggressive driving. Accid. Anal. Prev. **45**, 1–9 (2012)
15. Guo, M., Wei, W., Liao, G., Chu, F.: The impact of personality on driving safety among Chinese high-speed railway drivers. Accid. Anal. Prev. **92**, 9–14 (2016)
16. Stoichkov, R.: Android smartphone application for driving style recognition. Department of Electrical Engineering and Information Technology Institute for Media Technology (2013)
17. Fazeen, M., Gozick, B., Dantu, R., Bhukhiya, M., González, M.C.: Safe driving using mobile phones. IEEE Trans. Intell. Transp. Syst. **13**(3), 1462–1468 (2012)
18. Li, X., Jie, H., Jiang, H., Meng, W.: Establishing style-oriented driver models by imitating human driving behaviors. IEEE Trans. Intell. Transp. Syst. **16**(5), 2522–2530 (2015)
19. Syed, F., Nallapa, S., Dobryden, A., Grand, C., McGee, R., Filev, D.: Design and analysis of an adaptive real-time advisory system for improving real world fuel economy in a hybrid electric vehicle. Technical report, SAE Technical Paper (2010)
20. Murphey, Y.L., Milton, R., Kiliaris, L.: Driver's style classification using jerk analysis. In: 2009 IEEE Workshop on Computational Intelligence in Vehicles and Vehicular Systems, pp. 23–28. IEEE (2009)
21. Aguilar, J., Aguilar, K., Chávez, D., Cordero, J., Puerto, E.: Different intelligent approaches for modeling the style of car driving. In: Proceedings of the 14th International Conference on Informatics in Control, Automation and Robotics - Volume 2: ICINCO, pp. 284–291. INSTICC, SciTePress (2017)
22. Bongiorno, N., Bosurgi, G., Pellegrino, O., Sollazzo, G.: How is the driver's workload influenced by the road environment? Procedia Eng. **187**, 5–13 (2017)
23. Baldwin, C.L., Freeman, F.G., Coyne, J.T.: Mental workload as a function of road type and visibility: comparison of neurophysiological, behavioral, and subjective indices. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting, vol. 48, pp. 2309–2313. SAGE Publications Sage CA, Los Angeles, CA (2004)