**A Dynamic Behavior-centric Model for Driving Risk Assessment**

**Abstract**

*In this paper, a novel multilayer model is proposed for assessing driving risk. Studying driving behavior via massive driving data is essential for protecting road traffic safety and reducing losses of human life and property. In particular, identifying aggressive driving behavior and driving risk are multi-factors combined evaluation process, which must be processed with time and environment. For instance, improper time and environment may facilitate abnormal driving behavior. The proposed Dynamic Multilayer Model consists of identifying instant aggressive driving behavior that can be visited within specific time windows and calculating individual driving risk via DNN based classification algorithm. Validation results show that the proposed methods are particularly effective for classifying driving aggressiveness and risk level via real dataset of 2129 drivers’ driving behavior. (+ the necessity, significance of the research)*

**1. Introduction**

Reconstruct the introduction using following points:

1. The current situation/threats of driving. May be some research and figures as evidence. (same to scare or shock the readers. It will make the research interesting)
2. Current solution, or existing research and there flaws. Then you can add the sentence that the smart city and Internet of vehicle technology brought new opportunity to solve this problem.
3. The novelty and advantage of this paper.

With the development of Internet of vehicles (IOV), increasingly more organizations including government agents and IT companies are paying attention to leverage information technology and big data to improve driving safety.

Identifying and predicting driving risk will greatly benefit the research area of safety driving and driving risk control [1]. Driving risk assessment has been one of the major objectives in daily life for both individual drivers and insurance agents. During the last two decades, practitioners and scholars have been devoting themself to improve the effectiveness of identifying the driving risk level and predicting the driving behavior.

An accurate and effective driving risk assessment method could not only keep drivers safer but also bring more financial benefits for insurance agents and society. However, it is difficult to measure driving behavior in real-world driving situations [1] as driving styles vary among drivers. At the same time, this variation attracts researchers to study the classification of the drivers according to their risk levels. The variables such as demographic indicators, driver personalities and behaviors [2-4] are essential for evaluating driving risk level.

In recent years, technological advance of On Board Diagnostic (OBD) brings us a new insight to deal with this issue. Acquiring a comprehensive understanding of the OBD data could help researchers to reveal the individual driving behaviors [5]. A practicable data-driven classification model for driving risk assessment is needed and beneficial to traffic safety, traffic simulation and driving pattern recognition [6]. Hence, in this research, we propose a scenario based behavior-centric classification model for driving risk assessment using the real-world driving behavior data that collected from the OBD. To evaluate the proposed model, we compare the efficiency and effectiveness of it with benchmark methods.

This paper is organized as follows. Section 2 presents the related works. Section 3 proposes the behavior-centric driving risk classification model. Section 4 validates the model. Section 5 gives the conclusion to this paper.

**2. Literature review**

**2.1 Driving Risk Assessment**

**XXX(cite1)**

(+Difficulty to identify driving risk, For instance, safe speed in some place or time may be dangerous in others.)（常开路段常开时间有没有考虑——如果仅仅考虑了年龄、开车经验知识、性别等等，也许评估结果看起来较为平稳，但是当他常常进入特定路段如拥堵路段，或者。。。危险性其实就完全不一样；也许平均来看是平稳的，但是他在不同天气环境下行为又有不一样——考虑动态环境变化，结合实际实事求是）

**2.2 On-board device records for driving risk evaluation**

The potential variation in individual driving risk has been documented in prior studies [1, 7-9]. However, with the development of information technology and telecommunication, OBD systems have been incorporated into the computers on-board new vehicles to monitor vehicle components and driving behaviors in recent years.

The OBD system is designed to capture the detailed driving information such as vehicle speed, engine rpm, battery voltage, engine coolant temperature, diagnostic trouble codes, fuel consumption, etc. [10]. It gives the vehicle owner or repair technician access to the status of various vehicle subsystems. Researchers improved the efficiency of data usage from on-board devices by providing data collection and its applications [11]. Initial exposure of OBD data has a significant impact on driving behavior assessment [12, 13], and learning the feedback from driving behavior data has several benefits. For example, it can improve drivers’ driving behaviors and reduce fuel consumption [14]. With the development of OBD and the emergence of new techniques, more detailed understanding of these vehicle-related behavior records becomes possible, providing greater insight into individual driving behavior [5].

From the implication perspective of OBD, Shaout and Bodenmille [15] proposed a measurement and a prototype for inefficient and unsafe driving using OBD data. Similarly, Li et, al. [16] proposed a driving behavior monitoring and analysis system via OBD data records. The work proposed in Hong and Dey [17] generated an aggressive driving behavior assessment model based on the driving-related features provided by OBD and smartphones.

The work in [18] identified a qualitative driving behavior feature set with the in-car portable device data. They made an insightful comparison between the behavior data and the CAN-bus signal data. The results showed that detailed sensor data could achieve higher accuracies compared to the previous feature set.

The driving behavior features such as fuel consumption and driving style are closely related with each other [19, 20]. And the fuel consumption can be reduced by improving driving behavior [21]. Some other driving data extracted from OBD also have a strong power in reflecting driving behavior. For instance, vehicle speed, engine RPM, throttle position, and calculated engine load [11].

The influential parameters that are extracted from OBD in prior studies are summarized in Table 1. These variables are employed in many research directions such as behavior analysis, system designing, event recognition and driving improvement. Specifically, this study defines two categories of the OBD variables, namely, *unidirectional* and *bidirectional*. For a unidirectional variable, the numerical value of the parameter is linear to its abnormal degree. The value of a unidirectional variable has a positive (+) or negative (-) relationship with the abnormal degree directly. Take the variable *engine load* as an example, the burden of an engine will be higher with the numerical value of engine load increases. For bidirectional variable, the value is only considered as reasonable in a certain range. A value either higher or lower than the range will increase the abnormal degree of the variable. For instance, when engine temperature becomes too hot or too cold, it is considered as abnormal.

<Insert Table 1 about here>

**2.2 Driving behavior classification model**

Researchers from insurance and actuarial science investigated the driver classification according to their behavior risk level to facilitate auto insurance premium. These studies tried to predict driving risk based on driver’s age, gender, personality and some other relevant demographic variables [1, 22].

However, the keys of the driving risk assessment are not only driver demographic but also driving behavior analysis [11]. In terms of driving behavior classification methods, the Hidden Markov Model (HMM), Support Vector Machine (SVM), Decision Trees, Logistic Regression, Neural Network, Bayesian Networks and ensemble learning-based approach are usually adopted by researchers [11, 23-26].

Kumagai and Akamatsu [24] used to present a method of predicting driving behavior using Bayesian networks. Shi, Xu, Hu, Tang, Jiang, Meng and Liu [27] proposed a way of driving style identification and used neural networks to learn driver features and different driving styles. Similarly, Di Lecce and Calabrese [28] studied and classified the driving style into several categories using neural networks. In particular, a multilayer perceptron with back-propagation learning algorithm is used in their study. For the same purpose, Qi, Du, Wu and Xu [6] employed clustering method and topic model to extract latent driving states, in order to elaborate the commonness and individuality of behavior characteristics. They highlighted that the analysis of driving behaviors is very crucial. Multiple data mining techniques were adopted to analyze the driving behavior data collected by the instrumented vehicle, including ensemble clustering method based on the kernel fuzzy C-means algorithm and the modified latent Dirichlet allocation model.

Wang and Lukic [29] argued that driving style and driving condition are closely related to vehicle parameters such as fuel economy and emission reduction. They pointed out that statistic and cluster analysis, jerk analysis, Gaussian mixture models, and fuzzy classification methods can be used to identify drivers' driving styles. Wakita, Ozawa, Miyajima, Igarashi, Katunobu, Takeda and Itakura [30] proposed a driver identification method based on driving behavior signals of the accelerator pedal, brake pedal, vehicle velocity, and distance from the vehicle. Hong, Margines and Dey [17] used data and features extracted from smartphone and some other measurement units to characterize the driving behavior and predict the aggressive behaviors. The results indicated that more detailed driving data could help to achieve higher prediction accuracy through a machine learning method.

The authors of [18] used several techniques to evaluate the effectiveness of sensor information and to recognize driving behaviors. In their study, linear discriminant analysis is used for feature transformation. K-nearest neighbor algorithm and support vector machine are applied to classify the vehicle sensor information. Meanwhile, forward sequential feature selection is utilized for selecting the most influential subset of the features. In Shi, Yang, Jiang, Yang and Xiong [31]’s work, the authors proposed a very interesting driver identification framework for identifying a driver style by using inertial sensor data such as acceleration, location, and device touching. Chen, Pan and Lu [11] tried to analyze driving behavior via AdaBoost algorithms and the results showed that the behavior data is essential for classifying driving behavior. Guelman (2012) employed the Gradient Boosting classification method to predict auto accident cost with a real dataset obtained from a Canadian insurance company. The proposed method can train the model parameters with little data, and the experimental result has an advantage over the Generalized Linear Model approach. Fifteen location-based driving features were applied to three kinds of classification models for risk-level prediction in Paefgen’s study (there are 984 accident-free vehicles and 583 accident-involved vehicles in this case). The experimental results indicated that vehicle sensor data has great application potential to predict a driver’s insurance cost. The supervised neural network achieved the best performance for insurance cost estimation, while logistic regression classification has better fitness from an actuarial view [23].

As for driving environment, few prior researches indicated different driving risk standards for different road types. Meseguer, Calafate, Cano and Manzoni [32] implemented a neural network based algorithm that is able to detect the type of road on which the vehicle is moving. They divided the road type into 3 categories: urban, suburban and highway. However, the road conditions are sometimes different from each other even in one category. Besides, the analysis of road types should be more specific and detailed as the road condition and traffic flow in the same route can be changing every month, week and even every hour. Moreover, most prior works focused on the overall differences in driving behavior instead of behavior changing. However, a driver’s driving style and risk level vary. One point that has largely been overlooked in the literature is how to design a dynamic driving risk assessment system for evaluating driving behavior of individual drivers.

**References**

1 Guo, F., and Fang, Y.: ‘Individual driver risk assessment using naturalistic driving data’, Accident Analysis & Prevention, 2013, 61, pp. 3-9

2 Rhodes, N., and Pivik, K.: ‘Age and gender differences in risky driving: The roles of positive affect and risk perception’, Accident Analysis & Prevention, 2011, 43, (3), pp. 923-931

3 Miyajima, C., Nishiwaki, Y., Ozawa, K., Wakita, T., Itou, K., Takeda, K., and Itakura, F.: ‘Driver modeling based on driving behavior and its evaluation in driver identification’, Proceedings of the IEEE, 2007, 95, (2), pp. 427-437

4 Lajunen, T., and Summala, H.: ‘Driving experience, personality, and skill and safety-motive dimensions in drivers' self-assessments’, Personality and Individual Differences, 1995, 19, (3), pp. 307-318

5 Brackstone, M., and McDonald, M.: ‘Car-following: a historical review’, Transportation Research Part F: Traffic Psychology and Behaviour, 1999, 2, (4), pp. 181-196

6 Qi, G., Du, Y., Wu, J., and Xu, M.: ‘Leveraging longitudinal driving behaviour data with data mining techniques for driving style analysis’, IET intelligent transport systems, 2015, 9, (8), pp. 792-801

7 Ulleberg, P.: ‘Personality subtypes of young drivers. Relationship to risk-taking preferences, accident involvement, and response to a traffic safety campaign’, Transportation Research Part F: Traffic Psychology and Behaviour, 2001, 4, (4), pp. 279-297

8 Siordia, O.S., de Diego, I.M., Conde, C., Reyes, G., and Cabello, E.: ‘Driving risk classification based on experts evaluation’, in Editor (Ed.)^(Eds.): ‘Book Driving risk classification based on experts evaluation’ (IEEE, 2010, edn.), pp. 1098-1103

9 Simons-Morton, B., Lerner, N., and Singer, J.: ‘The observed effects of teenage passengers on the risky driving behavior of teenage drivers’, Accident Analysis & Prevention, 2005, 37, (6), pp. 973-982

10 Lin, J., Chen, S.-C., Shih, Y.-T., and Chen, S.-H.: ‘A study on remote on-line diagnostic system for vehicles by integrating the technology of OBD, GPS, and 3G’, World Academy of Science, Engineering and Technology, 2009, 56, pp. 435-441

11 Chen, S.-H., Pan, J.-S., and Lu, K.: ‘Driving Behavior Analysis Based on Vehicle OBD Information and AdaBoost Algorithms’, in Editor (Ed.)^(Eds.): ‘Book Driving Behavior Analysis Based on Vehicle OBD Information and AdaBoost Algorithms’ (2015, edn.), pp. 18-20

12 Godavarty, S., Broyles, S., and Parten, M.: ‘Interfacing to the on-board diagnostic system’, in Editor (Ed.)^(Eds.): ‘Book Interfacing to the on-board diagnostic system’ (IEEE, 2000, edn.), pp.

13 Toledo, T., and Lotan, T.: ‘In-vehicle data recorder for evaluation of driving behavior and safety’, Transportation Research Record: Journal of the Transportation Research Board, 2006, (1953), pp. 112-119

14 Toledo, G., and Shiftan, Y.: ‘Can feedback from in-vehicle data recorders improve driver behavior and reduce fuel consumption?’, Transportation Research Part A: Policy and Practice, 2016, 94, pp. 194-204

15 Shaout, A.K., and Bodenmiller, A.E.: ‘A mobile application for monitoring inefficient and unsafe driving behaviour’, University of Michig. n-Dearborn, 2011, 48128

16 Li, K., Lu, M., Lu, F., Lv, Q., Shang, L., and Maksimovic, D.: ‘Personalized driving behavior monitoring and analysis for emerging hybrid vehicles’, in Editor (Ed.)^(Eds.): ‘Book Personalized driving behavior monitoring and analysis for emerging hybrid vehicles’ (Springer, 2012, edn.), pp. 1-19

17 Hong, J.-H., Margines, B., and Dey, A.K.: ‘A smartphone-based sensing platform to model aggressive driving behaviors’, in Editor (Ed.)^(Eds.): ‘Book A smartphone-based sensing platform to model aggressive driving behaviors’ (ACM, 2014, edn.), pp. 4047-4056

18 Sathyanarayana, A., Sadjadi, S.O., and Hansen, J.H.: ‘Leveraging sensor information from portable devices towards automatic driving maneuver recognition’, in Editor (Ed.)^(Eds.): ‘Book Leveraging sensor information from portable devices towards automatic driving maneuver recognition’ (IEEE, 2012, edn.), pp. 660-665

19 Ericsson, E.: ‘Independent driving pattern factors and their influence on fuel-use and exhaust emission factors’, Transportation Research Part D: Transport and Environment, 2001, 6, (5), pp. 325-345

20 Van Mierlo, J., Maggetto, G., Van de Burgwal, E., and Gense, R.: ‘Driving style and traffic measures-influence on vehicle emissions and fuel consumption’, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 2004, 218, (1), pp. 43-50

21 Malikopoulos, A.A., and Aguilar, J.P.: ‘Optimization of driving styles for fuel economy improvement’, in Editor (Ed.)^(Eds.): ‘Book Optimization of driving styles for fuel economy improvement’ (IEEE, 2012, edn.), pp. 194-199

22 Segovia-Gonzalez, M., Guerrero, F., and Herranz, P.: ‘Explaining functional principal component analysis to actuarial science with an example on vehicle insurance’, Insurance: Mathematics and Economics, 2009, 45, (2), pp. 278-285

23 Paefgen, J., Staake, T., and Thiesse, F.: ‘Evaluation and aggregation of pay-as-you-drive insurance rate factors: A classification analysis approach’, Decis. Support Syst., 2013, 56, (1), pp. 192-201

24 Kumagai, T., and Akamatsu, M.: ‘Prediction of human driving behavior using dynamic bayesian networks’, IEICE TRANSACTIONS on Information and Systems, 2006, 89, (2), pp. 857-860

25 Guelman, L.: ‘Gradient boosting trees for auto insurance loss cost modeling and prediction’, Expert Systems with Applications, 2012, 39, (3), pp. 3659-3667

26 Bian, Y., Yang, C., Zhao, J.L., and Liang, L.: ‘Good drivers pay less: A study of usage-based vehicle insurance models’, Transportation Research Part A: Policy and Practice, 2018, 107, pp. 20-34

27 Shi, B., Xu, L., Hu, J., Tang, Y., Jiang, H., Meng, W., and Liu, H.: ‘Evaluating driving styles by normalizing driving behavior based on personalized driver modeling’, IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2015, 45, (12), pp. 1502-1508

28 Di Lecce, V., and Calabrese, M.: ‘Nn-based measurements for driving pattern classification’, in Editor (Ed.)^(Eds.): ‘Book Nn-based measurements for driving pattern classification’ (IEEE, 2009, edn.), pp. 259-264

29 Wang, R., and Lukic, S.M.: ‘Review of driving conditions prediction and driving style recognition based control algorithms for hybrid electric vehicles’, in Editor (Ed.)^(Eds.): ‘Book Review of driving conditions prediction and driving style recognition based control algorithms for hybrid electric vehicles’ (IEEE, 2011, edn.), pp. 1-7

30 Wakita, T., Ozawa, K., Miyajima, C., Igarashi, K., Katunobu, I., Takeda, K., and Itakura, F.: ‘Driver identification using driving behavior signals’, IEICE TRANSACTIONS on Information and Systems, 2006, 89, (3), pp. 1188-1194

31 Shi, W., Yang, J., Jiang, Y., Yang, F., and Xiong, Y.: ‘Senguard: Passive user identification on smartphones using multiple sensors’, in Editor (Ed.)^(Eds.): ‘Book Senguard: Passive user identification on smartphones using multiple sensors’ (IEEE, 2011, edn.), pp. 141-148

32 Meseguer, J.E., Calafate, C.T., Cano, J.C., and Manzoni, P.: ‘Drivingstyles: A smartphone application to assess driver behavior’, in Editor (Ed.)^(Eds.): ‘Book Drivingstyles: A smartphone application to assess driver behavior’ (IEEE, 2013, edn.), pp. 000535-000540

33 Hinton, G.E., Osindero, S., and Teh, Y.-W.: ‘A fast learning algorithm for deep belief nets’, Neural computation, 2006, 18, (7), pp. 1527-1554

34 Deng, L., and Yu, D.: ‘Deep learning: methods and applications’, Foundations and Trends® in Signal Processing, 2014, 7, (3–4), pp. 197-387

35 Hinton, G., Deng, L., Yu, D., Dahl, G.E., Mohamed, A.-r., Jaitly, N., Senior, A., Vanhoucke, V., Nguyen, P., and Sainath, T.N.: ‘Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups’, IEEE Signal Processing Magazine, 2012, 29, (6), pp. 82-97

36 Cortes, C., and Vapnik, V.: ‘Support-vector networks’, Machine learning, 1995, 20, (3), pp. 273-297

37 Ho, T.K.: ‘Random decision forests’, in Editor (Ed.)^(Eds.): ‘Book Random decision forests’ (IEEE, 1995, edn.), pp. 278-282

38 Åberg, L.: ‘Traffic rules and traffic safety’, Safety science, 1998, 29, (3), pp. 205-215

39 Paefgen, J., Staake, T., and Thiesse, F.: ‘Evaluation and aggregation of pay-as-you-drive insurance rate factors: a classification analysis approach’, Decision Support Systems, 2013, 56, pp. 192-201

40 Paefgen, J., Staake, T., and Fleisch, E.: ‘Multivariate exposure modeling of accident risk: Insights from Pay-as-you-drive insurance data’, Transportation Research Part A: Policy and Practice, 2014, 61, pp. 27-40

**Appendix 1 Table 1. Influential Instant Driving related Variables from OBD**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **Type** | **Studies** | | | | | | |
|  |  | Behavior Analysis | System designing | Accident risk accessing | Driving event recognition | Gas emission /Fuel-usage | Behavior improvement | Unsafe driving monitoring |
| [11] | [10] | [39, 40] | [18] | [19] | [14] | [15] |
| Location |  |  | \* | \* | \* | \* |  | \* |
| Speed | Bidirectional | \* | \* | \* |  | \* |  | \* |
| Engine load | Unidirectional (+) | \* |  |  |  |  |  |  |
| Throttle position | Bidirectional | \* |  |  |  | \* |  |  |
| Engine temperature | Bidirectional |  | \* |  |  | \* |  |  |
| Engine speed | Bidirectional | \* | \* |  |  | \* |  | \* |
| Miles per gallon | Unidirectional (-) |  |  |  |  |  |  | \* |
| Battery voltage | Bidirectional |  | \* |  |  |  |  |  |
| Diagnostic trouble codes | Unidirectional (+) |  | \* |  |  |  |  |  |
| Turns | Unidirectional (+) |  |  |  | \* |  |  |  |
| Orientation change | Unidirectional (+) |  |  |  | \* |  |  |  |
| Sudden break | Unidirectional (+) |  |  |  | \* | \* | \* |  |
| Acceleration | Unidirectional (+) |  |  |  |  | \* |  | \* |
| Deceleration | Unidirectional (+) |  |  |  |  | \* |  | \* |
| Positive kinetic energy | Unidirectional (+) |  |  |  |  | \* |  |  |
| Fuel usage | Unidirectional (+) |  |  |  |  | \* | \* |  |
| Emissions | Bidirectional |  |  |  |  | \* |  |  |

我们邀请这63位出租车驾驶员使用我们的软件，它检测到使用者的危险驾驶行为时将发出提醒，并在一天结束时提供驾驶行为评分排行。我们通过驾驶员们在软件中的签到情况来判断他们当天是否使用了我们的软件。