Analysis of drivers' characteristic driving operations based on combined features

Min Wang, Shuguang Li, Lei Zhu and Jin Yao
School of Manufacturing Science and Engineering, Sichuan University, Chengdu, China

Abstract

Purpose – Analysis of characteristic driving operations can help develop supports for drivers with different driving skills. However, the existing knowledge on analysis of driving skills only focuses on single driving operation and cannot reflect the differences on proficiency of coordination of driving operations. Thus, the purpose of this paper is to analyze driving skills from driving coordinating operations. There are two main contributions: the first involves a method for feature extraction based on AdaBoost, which selects features critical for coordinating operations of experienced drivers and inexperienced drivers, and the second involves a generating method for candidate features, called the combined features method, through which two or more different driving operations at the same location are combined into a candidate combined feature. A series of experiments based on driving simulator and specific course with several different curves were carried out, and the result indicated the feasibility of analyzing driving behavior through AdaBoost and the combined features method.

Design/methodology/approach – AdaBoost was used to extract features and the combined features method was used to combine two or more different driving operations at the same location.

Findings – A series of experiments based on driving simulator and specific course with several different curves were carried out, and the result indicated the feasibility of analyzing driving behavior through AdaBoost and the combined features method.

Originality/value – There are two main contributions: the first involves a method for feature extraction based on AdaBoost, which selects features critical for coordinating operations of experienced drivers and inexperienced drivers, and the second involves a generating method for candidate features, called the combined features method, through which two or more different driving operations at the same location are combined into a candidate combined feature.

Keywords Machine learning, Advanced driver assistant systems, Driver behaviors and assistance

Paper type Research paper

1. Introduction

With an increasing volume of automobiles, a number of traffic problems, including frequent traffic accidents and severe shortage of energy efficiency, are also on the rise (Sagberg *et al.*, 2015). The World Health Organization (2015) report on the status of global road safety stated that road traffic accidents were a major cause of death in the world and the leading cause of death among people of 15-29 years of age, with about 1.25 million people having died in 2013. To reduce traffic accidents and improve energy efficiency, many studies have been conducted with different results. For instance, Kato and Kobayashi (2008) found that fuel consumption could be reduced by 10-30 per cent while driving in eco-mode, which underscored the significance of driving behavior. Bingham *et al.* (2012) also found that calm drivers tend to have a lower fuel rate than aggressive drivers in similar situations. For the purpose of honing the skills of inexperienced drivers, research studies focused on driving skills by establishing a driver classification model. Wahab *et al.* (2009) applied the driving style questionnaire (DSQ) method to define individual driving styles and then collected driving data from drivers to train a classifier. Generally, the DSQ method needs a lot of time, efforts and resources to investigate driver behaviors. Aoude *et al.* (2012) divided the driving data into two driving styles (compliant and violating) and trained a classifier using a combination of the SVM-Bayesian filter (SVM-BF) and the hidden Markov model (HMM). Sundbom *et al.* (2013) collected the labeled data from drivers who drove normally or aggressively to train a classifier, based on a probabilistic autoregressive eXogenous model. Naiwala *et al.* used feature extraction and classifier modeling to establish a classification model of driver's driving skill when passing corners. They

The current issue and full text archive of this journal is available on Emerald Insight at: **www.emeraldinsight.com/2399-9802.htm**

Journal of Intelligent and Connected Vehicles
1/3 (2018) 114–119
Emerald Publishing Limited [ISSN 2399-9802]
[DOI 10.1108/JICV-09-2018-0009]

© Min Wang, Shuguang Li, Lei Zhu and Jin Yao. Published in *Journal of Intelligent and Connected Vehicles*. Published by Emerald Publishing Limited. This article is published under the Creative Commons Attribution (CC BY 4.0) licence. Anyone may reproduce, distribute, translate and create derivative works of this article (for both commercial and non-commercial purposes), subject to full attribution to the original publication and authors. The full terms of this licence may be seen at http://creativecommons.org/licences/by/4.0/legalcode

The authors thank Suda Laboratory at the University of Tokyo that provided them with experimental facilities, field and a part of the research grant. This work is also supported by "the Fundamental Research Funds YJ 201621 for the Central Universities" at Sichuan University and "the National Natural Science Foundation of China U1664263."

Received 20 September 2018
Revised 14 October 2018
Accepted 19 November 2018

adopted principal component analysis (PCA) to extract critical characteristics. And then, the discriminant model of driver's driving skill was established by using SVM, K-nearest neighbor (KNN) and probabilistic neural networks (PNN) (Chandrasiri *et al.*, 2010, 2012, 2016). Ly *et al.* (2013) also used a support vector machine (SVM) to recognize driving styles based on the labeled information of the vehicle's inertial sensors. To model and analyze driving styles semantically, Wang *et al.* (2017) gave a new framework for driving style analysis using primitive driving patterns with Bayesian nonparametric methods, a hierarchical structure (HDP-HSMM) was developed by combining hierarchical Dirichlet process (HDP) and hidden semi-Markov model (HSMM), which could learn a set of expected primitive driving patterns in car-following behaviors. Wang *et al.* (2017) used a k-means clustering method for drivers' labeling and applied a semi-supervised approach, namely, a semi-supervised support machine (S3VM), to classify various driving styles, the data labeling required a prior is greatly reduced and S3VM improved classification accuracy by about 10 per cent. Li *et al.* (2013, 2014) studied drivers' driving skills under a specific curve by using wavelet analysis to extract critical features and established the algorithm of experienced driver's behavior extraction based on AdaBoost. The above three studies were based on curved roads, using indirect features that reflected the potential specifics of practiced drivers and unpracticed drivers as candidate features. The studies analyzed drivers' lateral driving traits and longitudinal driving characteristics at the same time. Although drivers' driving skills can be better reflected in lateral and vertical operations under the cornering condition, the method of generating candidate feature results in a driving skill analysis only based on several single features, which cannot reflect driving skill on drivers' co-occurrence of driving operation; although signals of different frequency components can be found in the same feature, it is still limited to a single feature.

This paper took advantage of candidate combined features reflecting the consistency of driving operations; critical features were extracted using AdaBoost at the same time. Section 1 of this paper introduces the main achievements in terms of drivers' driving level. Section 2 involves a battery of experiments designed for driving data collection based on driving simulator. Section 3 describes data processing method and data analyzing approaches. Section 4 discusses relevant data analyzing result. Section 5 states the conclusions. The main research process is shown in Figure 1.

2. Experiment

This experiment was carried out with a driving simulator (DS) (Figure 2), which consisted of a visual system with a field of view of 140° around, a sound system and a dynamic model. The driving environment for the experiment (Figure 3) was a city road with six curves with left turn, and these curves, with different radiuses and lengths, were numbered 1-6 according to the travel direction (Figure 4). The speed limit of 60 km/h at 50 and 100 m before the start of each curve required drivers to maintain a speed of about 60 km/h before entering the curve. The collected data contained the position of accelerator and brake, front wheel angle, vehicle speed, lateral acceleration, longitudinal acceleration and yaw rate, with a sampling

Figure 1 Main research process

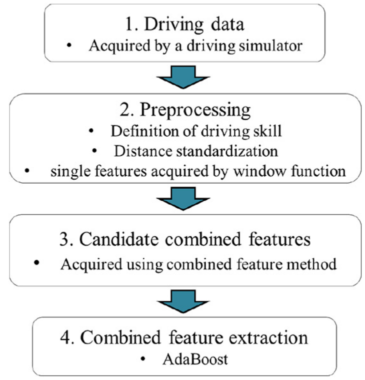


Figure 2 DS

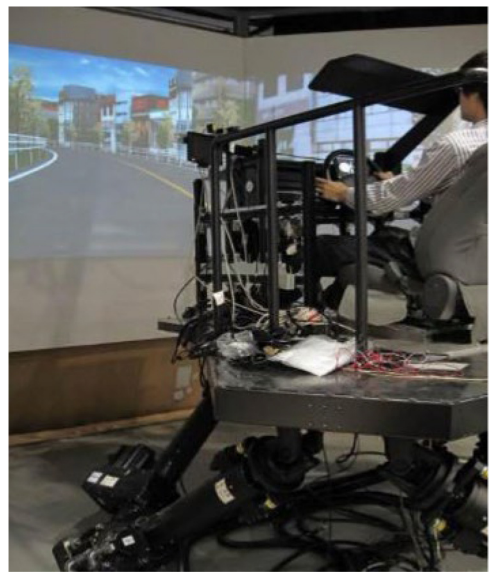


Figure 3 Road conditions of experiments

frequency of 60 Hz. To obtain sufficient experimental data, a total of 16 drivers of different driving levels participated in the experiment. Each driver completed 12 laps, the first two of which were test drives. Basic information of drivers is shown in Table I.

Figure 4 Driving route of experiments

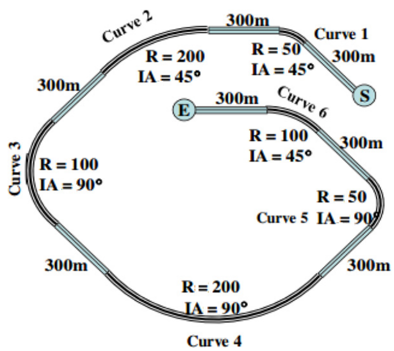


Table I Information of drivers

Drivers	Period of getting license (years)	Driving frequency (times/month)
1	4	0
2	20	5
3	19	0.2
4	3	1
5	10	0.4
6	11	8
7	4	0.5
8	7	7
9	3.5	1
10	6	0.5
11	3	1
12	3	4
13	24	20
14	1	1
15	5	0.1
16	13	1

2.1 Data normalization

All data collected on the basis of time were normalized with a certain distance according to the travel direction utilizing liner interpolation so that the same curve at different laps had comparability. The normalized data with the same data length are shown in Figure 5.

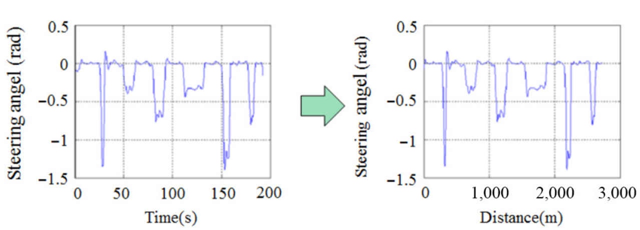
2.2 Driving skill labeled

Murphey *et al.* (2009) suggested that a smaller jerk or steady driving process would result in less fuel consumption and higher safety. This means that the smaller the jerk, the higher the driving skill. Complex jerk on behalf of a changed rate of acceleration at a distance was used for showing driver's driving skill in a curve. $\mathcal{J}$, representing the complex jerk, is given in equation (1). In the condition of the same average speed as described above, the bigger the variate $\mathcal{J}$, the lower the driving skill:

$$\mathcal{J} = \sum_{i=1}^{N} \sqrt{\mathcal{J}_{lateral-i}^2 + \mathcal{J}_{longitude-i}^2} \tag{1}$$

where $\mathcal{J}_{lateral-i}$ and $\mathcal{J}_{longitude-i}$ stand for lateral and longitudinal accelerations, respectively, at the i-th point in one curve and the variate N is the total number of standard points in the same curve.

Figure 5 Data before/after normalization



3. Method for data processing

3.1 Generation method for candidate combined features

Candidate combined features were decided by driving data, including steering wheel angle, accelerator petal position, brake petal position and corresponding operation and vehicle speeds. We chose the average in a distance of 9 m, which contained 30 standard points as candidate features, to decrease the error caused by operating occasionality, and the averages were extracted every other point:

$$y(P) = \begin{cases} 2 \text{ if } P_{i+1} - P_i > \Delta \\ 1 \text{ if } |P_{i+1} - P_i| \leq \Delta \\ 0 \text{ if } P_{i+1} - P_i < -\Delta \end{cases} \tag{2}$$

where variable y represents the change of single feature P.

This paper referred to the feature co-occurrence for face detection (Mita T *et al.*, 2005), which combined two or more different features into one feature, called the combined feature. The following gave the combined principle of two features at the same point: for a single feature P, the current feature P_{i+1} was compared with the previous adjacent feature P_i, and a threshold value Δ was set empirically for each kind of the feature P. Then, ternary numbers 2, 1 and 0 were used to indicate that the difference of P_{i+1} and P_i was greater than Δ, equal to Δ and less than Δ, respectively. The variable y for a sample P is figured in equation (2).

With the above processing for two features at a certain point of a certain curve, we could obtain a two-dimensional $N \times 2$ array, according to the rule of converting a ternary number into a decimal number [equation (3)], the ternary array of $n \times 2$ was converted to the decimal array of $n \times 1$ and the decimal array only contained the elements of 0-8, representing the nine kinds of candidate combined features, as shown in Table II:

$$G = 3\Delta_1 + \Delta_2 \tag{3}$$

where Δ_1 and Δ_2 are both ternary numbers.

3.2 Method for feature extraction

The feature extraction processing using AdaBoost is shown in Feature extraction processing using AdaBoost:

1. Given example of labeled data (x_1, y_1), (x_2, y_2), …, (x_n, yn),
   where $x_i \in X$, $y_i \in \{-1, +1\}$
2. Initialize weight $w_{i,t} = \frac{1}{N}$, $y_i = 0, 1$, where 0 and 1 are on behalf of experienced driver and

Table II Combined feature method

Combined feature G (Decimal number) \ Feature difference of a single feature P (Ternary number)	Δ1	Δ2
0	0	0*
1	0	1*
2	0	2*
3	1	0
4	1	1
5	1	2
6	2	0
7	2	1
8	2	2

Notes: *2 means $P_{i+1} - P_i > \Delta$, feature P increased; 1 means $|P_{i+1} - P_i| \leq \Delta$, feature P unchanged; 0 means $P_{i+1} - P_i < -\Delta$, feature P decreased

inexperienced driver respectively.

3. Iteration times $t = 1, 2, 3, \ldots, T$

3.1 The t-th weak classifier $H(x): X \rightarrow \{-1, +1\}$, its error rate ε_t is evaluated with respect to $w_t(i)$:

$$\epsilon_t = \sum_{t=1}^{N} w_t(i)\left[y_i \neq h_t(x_i)\right]$$

3.2 Weight of the t-th weak classifier $\alpha_t = \frac{1}{2}\ln\frac{1-\epsilon_t}{\epsilon_t}$

3.3 Update the weights of samples:

$$w_{t+1}(i) = \frac{w_t(i)\exp\left[-\alpha_t y_t h_t(x_i)\right]}{\sum_{i=1}^{N} w_t(i)\exp\left[-\alpha_t y_t h_t(x_i)\right]}$$

4. Strong classifier: $H(x) = sigh\left(\sum_{i=1}^{T} \alpha_t h_t(x)\right)$

Labeled data were $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$, where $y_i \in \{-1, +1\}$ corresponded to the label of variate x_i. As initialized weight was 1/N, weight would update once per iteration and be used in the next iteration. The last strong classifier $H(x) = sign(\alpha_t h_t(x))$ was a liner combination of a group of T weak classifiers. An optimal operation feature would be extracted per iteration until reaching the error threshold of classifier in step 3.

4. Result and discussion

4.1 Feature extraction

The relationship between number of weak classifiers and error rate of strong classifiers in Figure 6 was a critical step for deciding the number of weak classifiers using AdaBoost. The number of weak classifiers was the number of features extracted. We found that the error rate of strong classifiers was less than three per cent as the number of weak classifiers reached 15. This paper stipulated that when the accuracy of classifiers satisfied 97 per cent, the process for feature extraction was completed. Figure 7 shows the concrete locations of a part of the 15 features extracted. A major difference between skilled and unskilled drivers was obvious at the entrance. The details of those features are provided in Table III. For example, the first combined feature consisting of

Figure 6 Error rate of strong classifier at 1-th curve

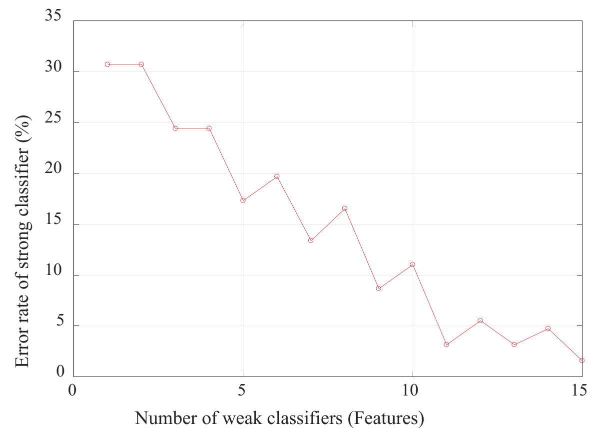
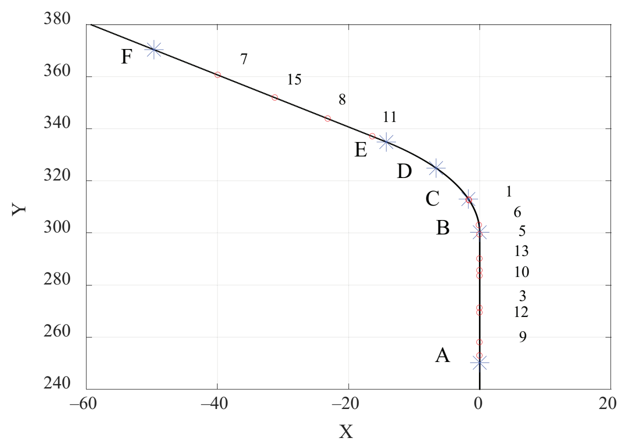


Figure 7 Driving features distribution at 1-th curve



velocity and steering angle appeared at the site that was 62.7 m away from the origin of 1-th curve, and the feature value of this combination was bigger than 1.5 as to inexperienced drivers.

4.2 Features distribution characteristics

Curves were divided into five parts, including 50 m before curve, 50 m after curve and trisection of the remaining curve in Figure 8. They were named sections AB, BC, CD, DE and EF along the travel direction. Figure 9 shows all features' distribution on the five sections of curved proposed above. Most features occurred at the entrance and exit, which were in line with actual driving as drivers got used to adjusting driving operations at those parts. In contrast, there were a few operations in the middle of the curves, seen in section CD. Combined features of "steering wheel operation speed and accelerator operation speed" and "accelerator petal position and steering wheel operation speed" were the most frequently extracted, which meant that the difference between the two groups of drivers was mainly in these two combined features.

In section AB, it was found that the combined feature of steering wheel angle and accelerator operation speed was more frequently extracted. In fact, drivers changed the steering wheel angle and velocity constantly at the entrance to adapt to the

Table III Basic information of features extracted at 1-th curve

No.	Feature name	Distance(m)	Threshold	Experience
1	Velocity and steering angle	62.7	1.5	Less
2	Brake and steering operation speed	62.4	4.5	Less
3	Brake and steering operation speed	21	4.5	Greater
4	Velocity and steering angle	33.3	1.5	Greater
5	Velocity and steering operation speed	49.2	0.5	Less
6	Steering operation speed and accelerator operation speed	52.8	7.5	Less
7	Steering operation speed and accelerator operation speed	124.8	3.5	Less
8	Velocity and steering operation speed	101.1	6.5	Greater
9	Steering angle and accelerator operation speed	7.8	3.5	Greater
10	Brake and steering operation speed	35.4	3.5	Less
11	Brake and steering operation speed	91.5	4.5	Less
12	Velocity and steering operation speed	19.2	1.5	Greater
13	Steering angle and accelerator operation speed	39.9	7.5	Greater
14	Steering angle and accelerator operation speed	2.7	4.5	Less
15	Steering angle and accelerator operation speed	112.5	4.5	Less

Figure 8 Curve segments

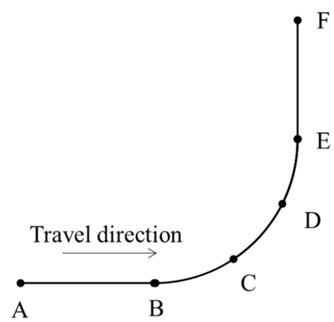
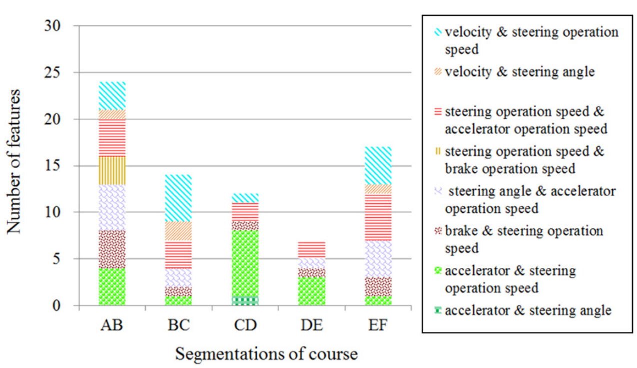


Figure 9 Features distribution in curve segments



changing course. The cause for the difference of the two groups in speed had first appeared via accelerator operation instead of velocity itself; thus, the adjustment of steering wheel angle and accelerator operation frequency most exhibited drivers' driving skills in section AB. With that, the operations on accelerator directly resulted in the imparity of velocity in the next section BC, and experienced and less experienced drivers differed greatly in section BC during the combined feature of velocity and steering operation speed. Accelerator and steering operation speeds became the predominant driving behavior in sections CD and DE. Drivers had accomplished the flexural road in section EF, skilled drivers mainly sped up and almost did not adjust the steering wheel angle, which reflected to driving operations were steering operation speed almost kept unchanged and accelerator operation speed changed, and this was the combined feature of steering operation speed and accelerator operation speed.

5. Conclusion

This paper proposed a method for driving operations characteristics analysis, using AdaBoost and feature co-occurrence. When the driving operations went through the curves at a special course, they were studied based on DS. In the end, all features corresponding to relevant curves were selected and extracted using the proposed method. The result illustrated that most features came out at the entrance and exit of all curves, which conformed to actual behavior when drivers entered or left curves.

We just studied driving feature extraction, which was a part of fundamental research in the field of driving operations characteristics. In the future, we plan to enrich the driving environment and not keep it restricted to courses consisting of curves alone. We are also keen to develop a driving assistant system that will help improve inexperienced drivers' driving skills through driving behavior analysis, so as to decrease traffic accidents.

References

Aoude, G.S., Desaraju, V.R., Stephens, L.H. and How, J.P. (2012), "Driver behavior classification at intersections and validation on large naturalistic data set", *IEEE Transactions on Intelligent Transportation Systems*, Vol. 13 No. 2, pp. 724-736.

Bingham, C., Walsh, C. and Carroll, S. (2012), "Impact of driving characteristics on electric vehicle energy consumption and range", *IET Intelligent Transport Systems*, Vol. 6 No. 1, pp. 29-35.

Chandrasiri, N.P., Nawa, K., Ishii, A., Li, S., Yamabe, S., Hirasawa, T., Matsumura, T., Sato, Y., Suda, Y. and Taguchi, K. (2012), "Driving skill analysis using machine learning the full curve and curve segmented cases", *International Conference on ITS Telecommunications IEEE*, pp. 542-547.

Chandrasiri, N.P., Nawa, K. and Ishii, A. (2016), "Driving skill classification in curve driving scenes using machine learning", *Journal of Modern Transportation*, Vol. 24 No. 3, pp. 1-11.

Chandrasiri, N.P., Nawa, K. and Kageyama, I. (2010), "Classification of driving skills base on machine learning", *FISITA World Automotive Congress*.

Kato, H. and Kobayashi, S. (2008), "Factors contributing to improved fuel economy in eco-drive", *Journal of Social Automotation Engineering Japan*, Vol. 62 No. 11, pp. 79-84.

Li, S., Yamabe, S., Sato, Y., Suda, Y., Chandrasiri, N.P. and Nawa, K. (2014), "Learning characteristic driving operations in curve sections that reflect drivers' skill levels", *International Journal of Intelligent Transportation Systems Research*, Vol. 12 No. 3, pp. 135-145.

Li, S., Yamabe, S., Hirasawa, T., Sato, Y., Hirasawa, T., Suda, Y., Chandrasiri, N.P. and Nawa, K. (2013), "Driving feature extraction from high and low skilled drivers in curve sections based on machine learning", *Journal of Mechanical Systems for Transportation and Logistics*, Vol. 6 No. 2, pp. 111-123.

Ly, M.V., Martin, S. and Trivedi, M.M. (2013), "Driver classification and driving style recognition using inertial sensors", *Proceedings in IEEE Intelligent Vehicles Symposium, Gold Coast*, pp. 1040-1045.

Mita, T., Kaneko, T. and Hori, O. (2005), "Joint haar-like features for face detection", *Proceedings*, Vol. 2 No. 2, pp. 1619-1626.

Murphey, Y.L., Milton, R. and Kiliaris, L. (2009), "Driver's style classification using jerk analysis", *Computational Intelligence in Vehicles and Vehicular Systems, CIVVS '09: IEEE Workshop*, pp. 23-28.

Sagberg, F., Piccinini, G.F.B. and Engstrom, J. (2015), "A review of research on driving styles and road safety", *Human Factors and Ergonomics Society*, Vol. 57 No. 7, pp. 1248-1275.

Sundbom, M., Falcone, P. and Sjoberg, J. (2013), "Online driver behavior classification using probabilistic ARX models", *Proceedings in 16th International IEEE Annual Conference Intelligence Transport Systems, Hague*, pp. 1107-1112.

Wahab, A., Quek, C., Tan, C.K. and Takeda, K. (2009), "Driving profile modeling and recognition based on soft computing approach", *IEEE Transactions on Neural Networks*, Vol. 20 No. 4, pp. 563-582.

Wang, W., Xi, J. and Zhao, D. (2017), "Driving style analysis using primitive driving patterns with bayesian nonparametric approaches", *IEEE Transactions on Intelligent Transportation Systems*,

Wang, W., Xi, J., Chong, A. and Li, L. (2017), "Driving style classification using a semisupervised support vector machine", *IEEE Transactions on Human-Machine Systems*, Vol. 47 No. 5, pp. 650-660.

World Health Organization (2015), *Global Status Report on Road Safety*, World Health Organization, pp. 4-5.

Corresponding author

Shuguang Li can be contacted at: lsg042@163.com

For instructions on how to order reprints of this article, please visit our website:
www.emeraldgrouppublishing.com/licensing/reprints.htm
Or contact us for further details: **permissions@emeraldinsight.com**