Estimation of driving style in naturalistic highway traffic using maneuver transition probabilities

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Abstract

Accurately estimating driving styles is crucial to designing useful driver assistance systems and vehicle control systems for autonomous driving that match how people drive. This paper presents a novel way to identify driving style not in terms of the durations or frequencies of individual maneuver states, but rather the transition patterns between them to see how they are interrelated. Driving behavior in highway traffic was categorized into 12 maneuver states, based on which 144 (12\times12) maneuver transition probabilities were obtained. A conditional likelihood maximization method was employed to extract typical maneuver transition patterns that could represent driving style strategies, from the 144 probabilities. Random forest algorithm was adopted to classify driving styles using the selected features. Results showed that transitions concerning five maneuver states – free driving, approaching, near following, constrained left and right lane changes – could be used to classify driving style reliably. Comparisons with traditional methods were presented and discussed in detail to show that transition probabilities between maneuvers were better at predicting driving style than traditional maneuver frequencies in behavioral analysis.

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1. Introduction

Driving style is generally defined as the habitual ways drivers choose to drive, i.e., the way individuals choose to drive or driving preferences that have developed over time (Elander et al., 1993; Lajunen and Özkan, 2011). Some definitions tend to emphasize ways of thinking (Ishibashi et al., 2007) or decision-making (Deery, 1999) rather than observable behavior. Despite the differences, these definitions are very much in accordance with each other in terms of their contents (Sagberg et al., 2015).

Driving style refers broadly to all activities performed by a driver, including strategic planning, tactical maneuvering, vehicle operation, as well as maintaining situation awareness and engaging in secondary tasks (Rasmussen, 1983; Cheng and Fujioka, 1997; Toledo et al., 2007). Fig. 1 summarizes the framework of driving style analysis. Strategic planning refers to knowledge-based activities, including the determination of route choice, the evaluation of the costs and risks involved, etc.
Tactical maneuvering is how a driver selects and performs specific driving tasks according to the strategic goal and the situational awareness of traffic and environment. Vehicle operation refers to the behaviors that the driver performs to control the vehicle, including steering, accelerating, braking, shifting gears, etc. Strategic, tactical, and operational activities have different time frames. Vehicle operation is usually at the milliseconds level, tactical maneuvering is at the seconds level, and strategic planning occurs over a longer time period, usually much longer (Michon, 1985). Situation awareness includes the perception of vehicle state and traffic environment with respect to time or space, understanding based on the perceived information, and prediction of the future situation (Stanton et al., 2001). Secondary tasks include phone-use, texting, smoking, eating, etc., which interfere with completion of the primary driving task.

Existing studies on driving style can be categorized using this framework. Studies of the strategic aspects of driving style include preferences for time-saving or short-distance routes, etc. (Dia, 2002). Studies of the tactical aspects of driving style consider maneuver preferences such as tailgating, frequently changing lanes, etc. (Ehsani et al., 2015). Studies of the operational aspects of driving style include preferences for rapid acceleration, hard braking, etc. (Toledo et al., 2008). Studies of the situation awareness aspects of driving style include the acceptance of long glances away from the forward scene, not checking for traffic before changing lanes, etc. (Birrell and Fowkes, 2014). Secondary task aspects include preferences of phone-use, texting, smoking or eating while driving, etc. (Ferdinand and Menachemi, 2014).

Existing studies emphasized that driving style mainly concerned with tactical and operational aspects (Bellem et al., 2016). They categorized driving behavior into driving maneuvers (e.g., following, hard braking, lane changing, etc.). These studies extended previous efforts in estimating driving style using a multifaceted representation of driving maneuvers, both independently and jointly. However, this paper focuses on exploring driving style estimation not in terms of the durations or frequencies of individual maneuver states, but rather the transition patterns between them to see how they are interrelated.

2. Related work

Studies have been conducted to examine the tactical and operational aspects of driving style. Previous research revealed that high-risk drivers drove faster, exhibited shorter time headways (THWs) with lead vehicles, braked harder, and changed lanes more frequently than low-risk drivers did in naturalistic driving (Xiong et al., 2012; Sagberg et al., 2015). Simons-Morton et al. (2015) and Kusano et al. (2015), from field operational tests, found that low-risk drivers engaged in fewer risky maneuvers (e.g., near following). Thus, these studies identified the differences in driving style between groups, but did not go the next step to create a model that estimated driving style.

In contrast, based on the number of detected maneuvers from naturalistic driving data on various roads in the United States, Guo and Fang (2013) classified drivers into three risk groups using K-means cluster method, and developed a logistic model to predict driving style. Their model showed that frequency of emergency braking events was an effective indicator of
high-risk drivers. Toledo et al. (2008) used in-vehicle data recorder to collect naturalistic driving data on various roads in Israel and developed pattern recognition algorithms to identify over 20 maneuver types (e.g., lane changes, sudden brakes). Risk indices were then proposed to classify drivers into three categories by combining the weighted maneuver frequencies. Validation tests demonstrated that the risk indices were effective in estimating driving style and reducing crash rate. Wang et al. (2015) extracted features from naturalistic emergency braking maneuvers on road types in China, based on which a classification and regression tree model was developed to estimate driving style. Drivers were classified into three risk groups using 9 rules. The overall estimation accuracy was only about 66% probably because only emergency braking maneuvers were used for estimation. Xu et al. (2015) classified drivers into three style groups and used neural network to model driving style using naturalistic driving data on highways in the United States. They developed driver models using operational signals, such as throttle and brake pedal position. Simulations were utilized to verify the effectiveness of the models.

Tactical maneuvers are primarily either longitudinal or lateral. See Fig. 2 for more details. Longitudinal maneuvers include: (1) free driving, (2) approaching, (3) following, (4) opening, and (5) emergency braking. Longitudinal maneuvers are classified into these categories based upon the values of THW, longitudinal acceleration, and the perception of changes in the apparent size of the vehicle ahead (Brackstone and McDonald, 1999; Toledo et al., 2007). More specifically, THW and longitudinal acceleration are commonly used to identify following maneuvers (Vogel, 2003; Kondoh et al., 2008). Perceiving if a vehicle is approaching, following, or opening depends upon the relationship of the relative velocity Δv to the changes on the visual angle θ subtended by the lead vehicle, given as \( d(Δv)/Δx^2 \) \( dt \), where Δx is the distance headway (Brackstone and McDonald, 1999).

Emergency braking is characterized by rapid deceleration, greater than 2 m/s\(^2\). Deceleration ranges within \((-2.0) m/s^2\). 98% of the highway driving time (Lee and Peng, 2005; Johnson and Trivedi, 2011). Further, when rapid deceleration is not occurring, a 3-s THW or less is considered to be car following (Transportation Research Board, 2010; Kusano et al., 2015). A driver following a lead vehicle with a THW longer than 3.0 s is considered to be a free driving maneuver. The thresholds for the perception of approaching and opening maneuvers are about \( 6.9 \times 10^{-4} \) and \(-5.2 \times 10^{-4}\), respectively (Brackstone and McDonald, 1999). Driving episodes with perception thresholds within \((-5.2, 6.9) \times 10^{-4}\) are considered to be following maneuvers. Driver minimum brake reaction times are approximately 0.8–1.3 s when following lead vehicles on highways (Isler and Starkey, 2010; Li et al., 2014). Therefore, drivers have ample time to respond when the following THW exceeds 2.0 s (assuming they are alert). Accordingly, following maneuvers can be categorized into three groups: near following (THW ≤ 1.0 s), middle following (1.0 < THW < 2.0 s) and far following (THW ≥ 2.0 s). See Ahmed (1999) and Salvucci (2006) for more details of longitudinal maneuvers.

The lateral maneuvers can be divided into free lane change and constrained lane change based on the presence of the lead vehicle, as suggested by Ahmed (1999). Considering the directional difference in lateral behavior (left and right), both free and constrained lane changes are further categorized into left and right sub-classes. SAE J2944 (2015) provides five alternative definitions for a lane change, with the definition depending upon when the change is assumed to begin and end. Option C defines a lane change as being the period from when a vehicle moves from a stable position in one lane to a stable position in another lane, with stable being defined as when the lateral velocity is 3.5 m/s or less. See Green (2013) for more details.

To date, most of the driving style studies either (1) treat driving maneuvers separately and individually, or (2) combine them together and weight each to compute an overall driving style score, without reporting the key indicators. These studies focus in greater detail on quantifying driving maneuvers or operations independent of time. Considering driving maneuvers over time as an indication of driving style, the transition probabilities between them can be indicators to estimate a driver’s driving style (Li et al., 2015b). Although there have been prior analyses of driving style using maneuver transition probabilities, this method has been used more successfully in the analysis of driver glance behavior, proving its effectiveness for driving behavior analysis (Birrell and Fowkes, 2014; Thorslund et al., 2014; Muñoz et al., 2015). This paper presents an innovative application of maneuver transition probabilities to driving style analysis.

Given the gaps in the literature, this study explores the relationship between driving style and driving maneuvers on highways, with respect to the following issues: (1) What are the transition probabilities between driving maneuvers? (2) Do the transition probabilities between maneuvers predict a driver’s driving style? The remainder of this paper is organized as follows: Section 3 introduces the experiment details, including the instrumented vehicle, test route, participants, etc. Section 4 proposes a model of maneuver transition probability and details the feature selection and classifier design techniques implemented in this study. Section 5 presents the results. Section 6 gives a discussion of the results. Section 7 concludes this paper.

The initial analysis of the experiment described in this paper appears in Li et al. (2015b). That paper focuses on a description of the maneuver durations and probabilities. This paper takes the analysis one step further, using that information to predict driving style.

3. Experiment

3.1. Vehicle instrumentation

The test vehicle used in this study was a full-size passenger car, with a 4.6 L internal combustion engine and a 5-speed automatic transmission. Six cameras were installed in the test vehicle to continuously monitor the surrounding traffic (cam-
era 2: front road images; camera 5: left blind zone images; camera 6: right blind zone images), the driver state (camera 3: face images), driver operations (camera 4: foot images), as well as the time headway (THW, camera 1) with the lead vehicle. See Figs. 3 and 4. This image collection system saved the images to a hard-disk recorder at 25 Hz. Another camera (camera 7), mounted on the front windshield, provided images of the front road scene for synchronizing the data with camera 2. Signals pertaining to vehicle state and driver operation were recorded from the CAN-bus, including vehicle speed, steering wheel angle, throttle position and brake pedal position. The data acquisition system saved both the CAN-bus data and channel 7 images at 10 Hz.

3.2. Test route

The test route was a section of the Jingha Highway (route G1), from Beijing to Xianghe in Hebei province in China. The section examined was three 3.5 m wide paved asphalt lanes in each direction. The traffic was light – the Level of Service was A and 10–15% of the traffic was heavy vehicles. The total round trip was about 146 km. The speed limit was 120 km/h. Participants were instructed to drive on the highway as they would during everyday driving.

An experiment assistant present in the vehicle all the times verbally gave participants the route guidance instructions following a predetermined script. This ensured all drivers received the same instructions. The assistant did not comment on how subjects drove (their style).

3.3. Participants

Licensed drivers were recruited to:

1. Be between ages 20 and 65.
2. Have at least 2 years of driving experience.
3. Have his/her own car.

The final sample consisted of 28 drivers (18 males and 10 females) with a mean age of 42.4 years ranging from 27 to 59 years old. A total of 4000 km of driving was accumulated during the experiment. On average, the subjects had 13.0 years driving experience, ranging from 2 to 33 years.

3.4. Test procedure

The participants were given a verbal explanation of the experiment prior to starting the test. The experiment started either at 10 AM in the morning or at 3 PM in the afternoon, with each round trip drive taking about 70 min. Data for rush hour or traffic jams was not collected.
3.5. Maneuver episode extraction

The episodes of the 11 maneuvers illustrated in Fig. 2 were extracted from the abovementioned highway traffic data in this study. Maneuvers not included in the framework were named as "others". Accordingly, 12 maneuver types were obtained – free driving, approaching, far/middle/near following, opening, free left/right lane change, constrained left/right lane change, emergency braking, and others.
To examine the tactical aspects of driving style, all maneuver episodes were manually identified frame-by-frame to determine the start and end times for each maneuver. Virginia Tech used a similar coding scheme for analysis of the 100-car field operational test data (Kusano et al., 2015; Campbell, 2012). Three driving safety researchers (coders) were trained to consistently segment maneuvers.

3.6. Subjective style evaluation

There are two ways to determine the driving style of a driver: (1) the crash rate experienced over many years, and (2) subjective evaluation by experts. The first method is not practical because of the cost of collecting and analyzing driving performance data from an individual driver over a long period of time. Alternatively, subjective evaluation by experts can be completed in less time using a smaller data set and has been preferred to assess driving style in previous studies (Elander et al., 1993; Taubman-Ben-Ari, 2006; Holman and Havârneanu, 2015).

To rate the driving style of each driver, a three-point scale (1 for low-risk; 2 for moderate-risk; 3 for high-risk) was used by three experts. All the three experts had extensive experience in the subjective evaluation of naturalistic driving videos. Individual driving style was labeled based on the probability the driver was going to be involved in a crash with other traffic participants (e.g., lead vehicle) (Elander et al., 1993). Experts were trained individually and then discussed and re-rated scenes viewed to get consistent ratings. Factors concerning crash probability usually include the preference for lane changing, preferred following headway time, etc.

Thus, each driver received three scores from the three experts (denoted by $E_A$, $E_B$, $E_C$). The final score of each driver depended upon whether the three experts agreed with each other or not. Eq. (1) shows the rules to calculate the final score, which defines the driving style of each driver. Subjective evaluation results showed that the difference between the expert scores never exceeded 1 in 93% of all the cases. The Cronbach’s alpha was 0.85, indicating high agreement between their evaluations.

\[
\text{Score} = \begin{cases} 
E_A, & \text{if } E_A = E_B = E_C \\
E_A, & \text{if } E_A = E_B \neq E_C, |E_A - E_C| \leq 1 \\
E_A, & \text{if } E_A = E_C \neq E_B, |E_A - E_B| \leq 1 \\
E_B, & \text{if } E_B = E_C \neq E_A, |E_A - E_B| \leq 1 \\
\text{rerate}, & \text{otherwise}
\end{cases}
\]

(1)

4. Method

4.1. Maneuver transition probabilities

This paper examines if the preferences to transition from one maneuver to another while driving are a good indicators of the tactical aspects of driving style. In this study, $\theta_i$ is defined as the current maneuver, and $\theta_j$ is defined as the next maneuver, defined as follows:

\[
\theta_i, \theta_j \in \{\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \theta_9, \theta_{10}, \theta_{11}, \theta_{12}\}
\]

\[
\begin{array}{cccccccccccc}
FD & AP & FF & MF & NF & OP & FL & FR & CL & LC & LC & LC & EB & OT \\
\end{array}
\]

where FD is for free driving, AP for approaching, FF for far following, MF for middle following, NF for near following, OP for opening, FLLC for free left lane change, FRLC for free right lane change, CLLC for constrained left lane change, CRLC for constrained right lane change, EB for emergency braking, and OT for others.

The transition probability from $\theta_i$ to $\theta_j$ for the driver is denoted by $a_{ij}$:

\[
a_{ij} = p(q_{t+1} = \theta_j|q_t = \theta_i) = \frac{\omega(q_{t+1} = \theta_j|q_t = \theta_i)}{\sum_{j=1}^{N} \omega(q_{t+1} = \theta_j|q_t = \theta_i)}
\]

(3)

where $q_t$ is the maneuver state at time $t$, $\omega$ is the number of transition events from $\theta_i$ to $\theta_j$, $a_{ij} \in [0, 1]$, $\sum_{j=1}^{N} a_{ij} = 1$, $N$ is the number of maneuver types, $1 \leq i,j \leq N$. In this study, $N = 12$. The transition matrix is defined as $A_t = \{a_{ij}\}$. If $a_{ij}$ approximates zero, the transition between those two maneuvers rarely occurs consecutively.

4.2. Feature selection

The transition probabilities between the maneuvers can form a feature set for classifier design. To select an optimized subset from the 144 ($12 \times 12$) transition features, a conditional likelihood maximization method based on mutual information is employed (Brown et al., 2012). This method incorporates the feature relevancy and redundancy concepts together to select the optimized subset by approximate iterative maximizers of the conditional likelihood. The optimized subset is a best
balance between the relevancy and redundancy of the 144 candidate features using the proposed framework. The criterion of feature selection using the joint mutual information (JMI) criterion (Meyer et al., 2008), which has been proved to be the best tradeoff in terms of accuracy, stability, and flexibility with small data samples, is:

\[
J_{\text{JMI}}(X_k) = \sum_{X_j \in S} I(X_k; X_j) = I(X_k; C) - \frac{1}{|S|} \sum_{X_j \in S} [I(X_k; X_j) - I(X_k; X_j|C)]
\] (4)

where \(X_k, X_j \in A, C \in \{\text{high-risk, moderate-risk, low-risk}\}, S\) is the set of features already selected. The algorithm selects kth feature \(X_k\) that maximizes the left-hand-side of the formulas. All entries of the right-hand-side of the formulas above can be divided into three categories according to their function: \(I(X_k; C)\) measures the correlation between terms \(X_k\) and driving style label \(C\), \(I(X_k; X_j)\) measures the redundancy between terms \(X_k\) and \(X_j\), and \(I(X_k; X_j|C)\) measures the complementariness between terms \(X_k\) and \(X_j\). For more details, please see Brown et al. (2012).

4.3. Classifier design

To determine the performance of various classifiers, Fernández-Delgado et al. (2014) evaluated 179 classifiers using 121 data sets, and found random forest was the best in terms of classification accuracy. “Random forest is a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest” (Breiman, 2001, page 5). The performance (e.g., generalization error) of a forest relies on the strength of the individual trees and the correlation between them.

Based on the selected features, driving style can be estimated using random forest algorithm. As illustrated in Fig. 5, a forest is an ensemble of \(M\) decision trees, each consisting of split and leaf nodes. Each split node consists of a feature \(X_k\) and a threshold \(c\). To classify feature vector \(X\), the current node is set to the root, and then the stop condition is evaluated. The current node is then updated to the left or right child according to the comparison \(f_{X_k}(X) < c\), and the process repeated until a leaf node is reached in tree \(m\). A learned distribution \(p_m(C|X)\) over driving style labels \(C\) is then stored at the leaf node reached in tree \(m\). The distribution is averaged together for all trees in the forest to give the final classification. The classifier to estimate driving style is shown as follows:

\[
p(C|X) = \frac{1}{M} \sum_{m=1}^{M} p_m(C|X)
\] (5)

5. Results

According to the results of subjective evaluation, the difference between the expert scores never exceeded 1 in 93% of all the cases. The driving styles of two drivers were discussed and re-rated by the experts. The Cronbach’s alpha was 0.85, indicating high agreement between their evaluations. The drivers were further categorized into three groups of driving style (high-, moderate-, and low-risk) based upon the final scores from the experts. Some 7 drivers were categorized into the low-risk group, 13 into the moderate-risk group, and 8 into the high-risk group.

5.1. Selected features from transition probabilities

The conditional likelihood maximization method was used to select an optimized sub-set of features from the 144 transition probabilities. The highest ranking five transition features were: (1) from near following to constrained right lane change, (2) from constrained right lane change to constrained left lane change, (3) from constrained left lane change to approaching, (4) from approaching to constrained right lane change, and (5) from constrained left lane change to free driving.

The differences between different style groups due to these five features are shown in Fig. 6. Statistical significance was found for the following transitions: (1) near following to constrained right lane change \((p < 0.001)\), (2) constrained right lane change to constrained left lane change \((p = 0.001)\), (3) constrained left lane change to approaching \((p = 0.007)\), and (4) constrained left lane change to free driving \((p = 0.048)\). These five features were also used for driving style estimation based on transition probabilities.

The transition probabilities between the maneuvers involved in the selected five features are presented in Fig. 7(a–c) for the low-, moderate-, and high-risk driving styles, respectively. The color indicates the transition probability value. The warmer the color is, the greater the probability the transition will occur.

Take constrained right lane change to constrained left lane change for example, the transition pattern means the driver changed lanes and then immediately changed again. See Fig. 8. The transition could be divided into two phases. Phase 1 indicates a constrained right lane change, immediately following by a constrained left lane change (phase 2). This maneuver sequence is usually used to pass a slow moving lead vehicle by high-risk drivers.
5.2. Driving style classification

A random forest classifier was developed based on the selected five transition probability features. The leave-one-out method was applied for cross validation. The correct classification rate of the classifier could then be measured. When the number of trees reached 30, the correct classification rate was maximized.

The recognition result is shown in Table 1. All the low- and high-risk driving style samples were recognized correctly. Eleven out of the 13 moderate-risk drivers were classified correctly, whereas one out of the other two drivers was recognized as a low-risk driver and the other one as a high-risk driver. The overall correct recognition rate was 93%. The correlation between the subjective risk evaluation scores and the probability of being a high-risk driver was 0.84, significant at the 0.01 level.

As shown in Table 1, driving style can usually be reliably determined using the selected five transition features. However, compared with low- and high-risk driving styles, moderate-risk style was more difficult to identify. As shown in Fig. 6, moderate-risk drivers transited from constrained right lane change to constrained left lane change with a greater probability than for low-risk drivers. The difference in the probabilities between moderate- and high-risk drivers was not statistically significant. Thus, from this aspect, moderate-risk drivers could be categorized into the high-risk group. Similarly, moderate-risk drivers transited from near-following or approaching to constrained right lane change with probabilities similar to that of low-risk drivers. Thus, from this aspect, moderate-risk drivers could be categorized into the low-risk group. These contradictions made the identification of moderate-risk driving style more difficult than that of low- and high- driving styles, and needed to be further balanced.

6. Discussion

Previous studies of driving style estimation examined maneuver frequency, or duration, or the percentage of total driving time for each maneuver (Sagberg et al., 2015). Table 2 presents the differences between driving style groups for these three

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Fig. 5. Random forest algorithm. A forest is an ensemble of trees. Each tree consists of split nodes (blue) and leaf nodes (green). The red arrows indicate the different paths that might be taken by different trees for a particular input. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 6. Maneuver transition probability differences between low- and high-risk drivers for the five critical features. (FD: free driving; AP: approaching; NF: near following; CLLC: constrained left lane change; CRLC: constrained right lane change).
measures for all the 12 maneuvers. The maneuver frequency is the number of times each maneuver occurred per 100 km driving on highway. High-risk drivers spent significantly more time in approaching ($p = 0.022$), and constrained lane changes (left: $p = 0.005$, right: $p < 0.001$), but less time in free driving ($p = 0.003$) than low-risk drivers. Statistically significant differences in maneuver frequencies between driving style groups were found for approaching ($p < 0.001$), middle following
(p = 0.001), near following (p = 0.030), and constrained lane change (left: p = 0.002; right: p < 0.001). The statistically significant differences in maneuver durations between the driving style groups were found for free driving (p < 0.001), approaching (p = 0.026), and free left lane change (p = 0.001). Again, for additional analysis and details concerning maneuver frequency and duration, see Li et al. (2015b), the predecessor paper upon which this article builds.

These maneuver differences between different groups imply that maneuver frequency is the best feature to estimate driving style. Five variables (maneuver frequencies of approaching, middle following, near following, constrained left and right lane change) were selected as the feature vector to develop a driving style classifier using a random forest algorithm. The same tree number (n = 30) was used. The consistent classification method was employed as used in the previous section.

The classification result is shown in Table 3. All the low- and high-risk style samples were recognized correctly. Six out of the 13 moderate-risk drivers were classified correctly, whereas two out of the other seven drivers were recognized as low-risk drivers and the other five as high-risk drivers. The overall correct recognition rate was 75%, not as good as the results when using transition probabilities. The correlation of 0.76 between the subjective risk evaluation scores and the probability of being a high-risk driver was significant at the 0.01 level.

The transition probabilities between maneuvers focus on exploring driving style patterns beyond isolated maneuvers to show how they are interrelated, not in terms of the individual maneuvers themselves. From the perspective of feature relevance and redundancy, the transition probability features achieved a good balance between these two characteristics. Table 4 shows the Pearson correlation coefficients between the five maneuver frequencies. The correlation coefficients between the five transition probabilities are shown in Table 5. The lower correlation values between the transition probabilities and lower significance levels establish the effectiveness of the method used in this study.

As shown in Table 2, high-risk drivers approached lead vehicles 127% more often than low-risk drivers. Only 3 near following episodes were observed for all the low-risk drivers, whereas 60 occurred for the high-risk drivers. For lane change maneuvers, although approximately the same number of free left and right lane changes occurred every 100 km for both low- and high-risk drivers, the number of constrained lane changes differed between the risk groups. High-risk drivers performed constrained lane changes approximately three times the number of low-risk drivers. Derived from the data shown in Table 2, the mean number of lane changes (combining free and constrained lane changes) was about 23 and 45 per 100 km for low- and high-risk drivers, respectively. However, in comparison, the mean number was about 22 for U.S. drivers on highways (Olsen et al., 2002). Thus, on average, Chinese drivers drove more aggressively than comparable U.S. drivers on highways (Lindgren et al., 2008). Comparable studies between Chinese and U.S. drivers indicated that driver attitudes towards traffic safety needed to be improved in China (Huang et al., 2006; Zhang et al., 2006).

Practical applications of the findings in this study include: (1) helping automotive industries manufacturers and suppliers design vehicles consumers will want by providing them with the information needed to personalize driving assistance systems to match individual driving styles (Cho et al., 2006; Chen et al., 2013; Qi et al., 2015; Li et al., 2015a); (2) designing human-like automated vehicle control systems (Vanholme et al., 2013; Bellem et al., 2016); (3) setting insurance rates based upon the driving style of a driver (Troncoso et al., 2011; Desyllas and Sako, 2013); and (4) providing other benefits to drivers themselves (reduced fuel consumption, decreased vehicle maintenance bills, identifying impaired driving to reduce crash risk, training and education, personalizing in-vehicle information systems, etc.) (Ma et al., 2015).

The limitations of this study lie in the limited amount of observed driving data and few consideration of congested city traffic. Future research should focus on the following topics: First, the amount of observed driving data influence the ability to detect a driver’s driving style. As more new datasets are taken into account, it is more possible to get a complete knowledge about the driving style of a driver with the proposed method which is highly dependent on data. Second, maneuver

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**Table 1**

<table>
<thead>
<tr>
<th>Expert risk classification</th>
<th>Recognized by classifier as</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low-risk</td>
</tr>
<tr>
<td>Low-risk</td>
<td>7/7</td>
</tr>
<tr>
<td>Moderate-risk</td>
<td>1/13</td>
</tr>
<tr>
<td>High-risk</td>
<td>0/8</td>
</tr>
</tbody>
</table>

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*Fig. 8. An example of maneuver transition patterns.*
transitions in city traffic need to be analyzed. With congestion, it is expected that transition probabilities should continue to be a best determinant for driving style, although congestion may alter the individual values. As congestion increases, delays due to lead vehicles could induce drivers with aggressive styles to change lanes more often. However, traffic may become so congested that changing lanes becomes difficult and transitions, such as between following states, become more important. As opposed to the highway driving examined in this paper, Fig. 9 indicates the more complex structure needed to examine driving style in city traffic context. Data for that purpose could be collected and evaluated in future studies using the methods described in this paper. Third, the variability in driving styles by driver varies. Drivers may behave differently in different

<table>
<thead>
<tr>
<th>% of total driving time</th>
<th>Maneuver frequency (number of events per 100 km)</th>
<th>Duration (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low (L)</td>
<td>Moderate (M)</td>
<td>High (H)</td>
</tr>
<tr>
<td>FD</td>
<td>56.8 (8.4)</td>
<td>35.2 (13.3)</td>
</tr>
<tr>
<td></td>
<td>41.4 (11.6)</td>
<td>0.003**</td>
</tr>
<tr>
<td>AP</td>
<td>9.3 (4.5)</td>
<td>15.6 (5.5)</td>
</tr>
<tr>
<td></td>
<td>15.1 (3.1)</td>
<td>0.022</td>
</tr>
<tr>
<td>FF</td>
<td>8.2 (5.4)</td>
<td>8.6 (3.6)</td>
</tr>
<tr>
<td></td>
<td>5.9 (6.1)</td>
<td>0.465</td>
</tr>
<tr>
<td>MF</td>
<td>5.0 (5.3)</td>
<td>8.1 (3.6)</td>
</tr>
<tr>
<td></td>
<td>5.4 (2.6)</td>
<td>0.167</td>
</tr>
<tr>
<td>NF</td>
<td>0.1 (0.2)</td>
<td>2.5 (1.8)</td>
</tr>
<tr>
<td></td>
<td>5.1 (5.5)</td>
<td>0.087</td>
</tr>
<tr>
<td>OP</td>
<td>9.6 (5.8)</td>
<td>18 (13.3)</td>
</tr>
<tr>
<td></td>
<td>8.2 (6.5)</td>
<td>0.079</td>
</tr>
<tr>
<td>FLLC</td>
<td>1.7 (1.0)</td>
<td>1.7 (1.0)</td>
</tr>
<tr>
<td></td>
<td>2.6 (1.3)</td>
<td>0.168</td>
</tr>
<tr>
<td>FRLC</td>
<td>1.8 (0.6)</td>
<td>1.4 (1.5)</td>
</tr>
<tr>
<td></td>
<td>1.1 (0.7)</td>
<td>0.449</td>
</tr>
<tr>
<td>CLLC</td>
<td>2.3 (1.2)</td>
<td>3.1 (1.8)</td>
</tr>
<tr>
<td></td>
<td>5.3 (2.0)</td>
<td>0.005**</td>
</tr>
<tr>
<td>CRLC</td>
<td>1.9 (1.1)</td>
<td>3.4 (2.0)</td>
</tr>
<tr>
<td></td>
<td>6.6 (2.4)</td>
<td>&lt;0.001**</td>
</tr>
<tr>
<td>FL</td>
<td>2.2 (1.9)</td>
<td>1.9 (1.1)</td>
</tr>
<tr>
<td>EB</td>
<td>2.2 (1.9)</td>
<td>1.9 (1.1)</td>
</tr>
<tr>
<td>OT</td>
<td>0.9 (1.3)</td>
<td>0.6 (0.4)</td>
</tr>
</tbody>
</table>


| Significance at 0.05 level. ** Significance at 0.01 level. |

Table 3
Classification result using maneuver frequencies.

<table>
<thead>
<tr>
<th>Expert risk classification</th>
<th>Recognized by classifier as</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-risk</td>
<td>Moderate-risk</td>
</tr>
<tr>
<td>Low-risk</td>
<td>7/7</td>
</tr>
<tr>
<td>Moderate-risk</td>
<td>2/13</td>
</tr>
<tr>
<td>High-risk</td>
<td>0/8</td>
</tr>
</tbody>
</table>

Table 4
Pearson correlation coefficients between frequencies of the five maneuvers.

<table>
<thead>
<tr>
<th>Correlation</th>
<th>AP</th>
<th>MF</th>
<th>NF</th>
<th>CLLC</th>
<th>CRLC</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP</td>
<td>1</td>
<td>0.47**</td>
<td>0.51**</td>
<td>0.41</td>
<td>0.55</td>
</tr>
<tr>
<td>MF</td>
<td>0.47</td>
<td>1</td>
<td>0.26</td>
<td>0.23</td>
<td>0.15</td>
</tr>
<tr>
<td>NF</td>
<td>0.51**</td>
<td>0.26</td>
<td>1</td>
<td>0.21</td>
<td>0.43</td>
</tr>
<tr>
<td>CLLC</td>
<td>0.41</td>
<td>0.23</td>
<td>0.21</td>
<td>1</td>
<td>0.88</td>
</tr>
<tr>
<td>CRLC</td>
<td>0.55</td>
<td>0.15</td>
<td>0.43</td>
<td>0.88</td>
<td>1</td>
</tr>
</tbody>
</table>

* Significance at 0.05 level. ** Significance at 0.01 level.

Table 5
Pearson correlation coefficients between the five transition probabilities.

<table>
<thead>
<tr>
<th>Correlation</th>
<th>NF-CRLC</th>
<th>CRLC-CLLC</th>
<th>CLLC -AP</th>
<th>AP-CRLC</th>
<th>CLLC-FD</th>
</tr>
</thead>
<tbody>
<tr>
<td>NF-CRLC</td>
<td>1</td>
<td>0.19</td>
<td>0.47*</td>
<td>0.38*</td>
<td>−0.33</td>
</tr>
<tr>
<td>CRLC-CCLLC</td>
<td>0.19</td>
<td>1</td>
<td>0.42*</td>
<td>0.08</td>
<td>−0.39*</td>
</tr>
<tr>
<td>CLLC -AP</td>
<td>0.47*</td>
<td>1</td>
<td>1</td>
<td>0.13</td>
<td>−0.50**</td>
</tr>
<tr>
<td>AP-CRLC</td>
<td>0.38*</td>
<td>0.08</td>
<td>0.13</td>
<td>1</td>
<td>−0.37</td>
</tr>
<tr>
<td>CLLC-FD</td>
<td>−0.33</td>
<td>−0.39*</td>
<td>−0.50**</td>
<td>−0.37</td>
<td>1</td>
</tr>
</tbody>
</table>

* Significance at 0.05 level. ** Significance at 0.01 level.
situations because of time pressure, driving mood, road anger, presence of other passengers, etc. (Shinar and Compton, 2004; Kim et al., 2013). For example, a low-risk driver may adopt a high-risk driving style when he/she is in a hurry to get to the airport. Thus, the driving style a driver performs in a single trip (trip-level driving style) may not completely represent his/her driving style under all circumstances. The driving styles analyzed in this study are trip-level styles. One interesting approach to modeling and estimation of driver-level driving style would be to utilize data mining techniques to examine existing databases of naturalistic driving data.

7. Conclusions

This paper presents a method to estimate driving style in highway traffic using the transition probabilities between 12 maneuvers. High-risk drivers were more likely to be involved in approaching, near following, and constrained left and right lane changes. The highest ranking five transition probability features to estimate driving style were: (1) from near following to constrained right lane change, (2) from constrained right lane change to constrained left lane change, (3) from constrained left lane change to approaching, (4) from approaching to constrained right lane change, and (5) from constrained left lane change to free driving. Better estimation accuracy of driving style was found using maneuver transition probabilities, compared with a traditional method using maneuver frequencies. These efforts extend previous research that focus in greater detail on quantifying maneuver independent of time. Leveraging maneuver transition probabilities to predict driving style provides a novel perspective for future naturalistic driving studies.

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References
