Evaluation Method for Aggressiveness of Driving Behavior Using Drive Recorders

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(Manuscript received March 13, 2014, revised Aug. 9, 2014)

In this paper, we propose an automated method for measuring the aggressiveness of driving behavior by using driving signals from drive recorders. Currently, some risk consulting companies have experts review recorded driving behavior and then rate the drivers empirically. This approach is time-consuming and expensive, however, so an effective automated driver evaluation method is desired. We assumed that the aggressiveness of a driver’s behavior can be determined by focusing on four types of vehicle operation behavior: steering, acceleration, deceleration, and alternation between acceleration and deceleration. Aggressiveness scores can be assigned to each of these behaviors, and a driver’s overall aggressiveness score is then estimated by integrating these behaviors using multiple linear regression. We assessed the aggressiveness of 78 drivers and compared our assessments to the aggressiveness scores assigned empirically by the risk consulting experts. The proposed method achieved a rank correlation coefficient of 0.74 with the evaluations of the risk consulting experts.

Keywords: driving behavior evaluation, drive recorders, aggressive driving, multiple linear regression, principal component analysis

1. Introduction

Between 2003 and 2007, up to 56% of fatal automobile crashes involved unsafe driving behavior, especially behavior associated with aggressive driving, according to a report by the American Automobile Association Foundation for Traffic Safety (1), and similar findings have also been reported in publications of the U.S. National Highway Traffic Safety Administration (NHTSA) (2). According to a report released by the Japanese Ministry of Land, Infrastructure, Transport and Tourism in 2012, 31.7% of serious traffic accidents involving taxis, trucks, and buses were caused by improper vehicle operation (3), such as driving at excessive speeds, running stop signs and red lights, making improper turns, and tailgating behaviors which are associated with aggressive driving. Aggressive driving also results in increased fuel consumption, as a result of rapid acceleration and deceleration; approximately 33% higher fuel consumption at highway speeds, and 5% higher when driving in town (4). Aggressive driving, therefore, creates both safety and resource use issues for automobile-based societies. On the other hand, it has been reported that by monitoring driving behavior with drive recorders mounted on vehicles and sharing the evaluation results with drivers, driver safety awareness can be increased and aggressive driving behavior can be reduced (5). One study has shown that the number of traffic accidents could be reduced by 30 to 80% using this method (6). However, the current method of driving behavior evaluation, which involves the use of risk consulting experts to empirically evaluate drivers, is time-consuming and costly, and so an automated method of evaluating driver behavior is needed.

Thanks to the proliferation of small devices such as drive recorders and smartphones in recent years, many kinds of driving behavior signals, such as vehicle velocity and acceleration, have become easier to record, and these recorded signals can be very useful for automatic analysis of driving behavior. Naito et al. evaluated risk levels of driving behavior, focusing on deceleration patterns while braking (7). Miyajima et al. identified risky driving behavior by independently evaluating steering behavior, acceleration behavior, and deceleration behavior (8). However, no unified driving behavior evaluation method was developed in their research. Johnson et al. developed a method of evaluating driving behavior using driving behavior signals collected with a smartphone. Driving styles were divided into two categories, non-aggressive and aggressive, based on a driving event recognition technique (9). In contrast to previous methods of driving behavior evaluation, in this study we propose a quantitative method of evaluating the overall aggressiveness of driving behavior.

Although researchers have defined aggressive driving behavior in various ways (10)–(11), in this study we assume that by observing a driver’s operation of the steering wheel, gas pedal, and brake pedal, driving behavior can be evaluated. We use four vehicle operation behaviors, namely, steering behavior, acceleration behavior, deceleration behavior, and alternation between acceleration and deceleration, to quantify the aggressiveness of a driver’s behavior. Thus, we can describe driving behavior by simply using three driving signals; vehicle velocity, longitudinal acceleration, and lateral acceleration.

In order to determine the overall aggressiveness of a driver’s behavior, we use the aggressiveness scores of the four vehicle operation behaviors mentioned above. The
aggressiveness of steering behavior is measured using vehicle speed and the minimum radius of road curvature as specified by a road construction ordinance (12). In order to measure the aggressiveness of acceleration behavior, we use a two-dimensional plane to compare maximum longitudinal vehicle acceleration and vehicle velocity when maximum acceleration is observed. The aggressiveness of deceleration behavior is measured by observing the frequency of rapid braking. To measure alternation between acceleration and deceleration, we use vehicle velocity, longitudinal acceleration, and jerk. These four quantitative measures of aggressiveness are then used to estimate the overall aggressiveness of a driver’s behavior. Using recorded driving data from 78 drivers of company vehicles, we then evaluate our method experimentally by comparing our results to those of risk consulting experts, who empirically evaluated the aggressiveness of the same drivers using the same recorded data.

In the following section, we introduce our method to measure aggressiveness of driving. An experiment of driving behavior aggressiveness prediction is presented in Sect. 3. Our conclusions and suggestions for future work are presented in Sect 4.

2. Evaluation of Driving Behavior

To evaluate the aggressiveness of a driver’s behavior, we use three kinds of driving signals, i.e., vehicle velocity, longitudinal acceleration, and lateral acceleration. We assume that these signals can then be used to represent four vehicle operation behaviors, i.e., steering behavior, acceleration behavior, deceleration behavior, and alternation between acceleration and deceleration. Driving data related to each of these driving behaviors is collected and used to estimate the aggressiveness scores of each behavior. We then integrate the aggressiveness scores of these behaviors to estimate a driver’s overall driving aggressiveness score. The method of obtaining an aggressiveness score for each operation behavior is discussed in Sects. 2.1 through 2.4. The overall aggressiveness of a driver’s behavior is then calculated by applying multiple regression to the aggressiveness scores for the four operation behaviors.

It should be noted, however, that the vehicle operation behaviors may not be completely independent of one other. Alternation between acceleration and braking, for example, may be associated with acceleration behavior and deceleration behavior. Associations may also exist among other features of aggressiveness, which may cause multi-collinearity during multiple regression (13). In addition, feature correlation may reduce the prediction performance of the regression model. Therefore, we also use principal component regression (PCR) (14), which applies principal component analysis (PCA) to the features of each driving behavior prior to linear regression. We assume that a driving aggressiveness score (S) can be represented as a regression model, which is defined as:

\[ S = a_0 + a_1p_1 + a_2p_2 + ... + a_np_n, \] (1)

where \( a_i \) is the regression coefficient, and \( p_i \) is the explanatory variable of the \( i \)-th feature or principal component. We use the driving behavior features listed in Table 1 to measure aggressiveness in this study.

| Sub-behavior   | Symbol | Feature                          |
|----------------|--------|----------------------------------|
| Steering behavior | \( f_s \) | Proportion of abrupt steering operations |
| Acceleration behavior | \( f_a \) | Acceleration from stop             |
| Deceleration behavior | \( f_d \) | Driver’s preferred speed           |
| Alternation behavior | \( f_a \) | Standard deviation of velocity |
|                 | \( f_d \) | Standard deviation of acceleration |
|                 | \( f_j \) | Standard deviation of jerk         |

The following sub-sections explain the meaning of each feature and how these features are extracted from the corresponding driving signals.

2.1 Steering Behavior

We assume that steering behavior is aggressive if it results in a smaller radius of curvature than the minimum radius considered to be safe at that speed, according to Japanese road construction ordinance No. 15 (15). Exact values for maximum safe speeds at different radii of curvature are shown in Table 2. As this table shows, larger minimum radii of road curvature are required to safely accommodate vehicles traveling at higher speeds.

The proportion of abrupt steering operations in relation to overall steering operations is used as a feature to indicate the aggressiveness of steering behavior (\( f_s \)). Here, we approximate vehicle motion while steering as a circular motion, and estimate the radius of the curvature of vehicle trajectory (\( R \)) based on the following circular motion equation:

\[ R = \frac{v^2}{a}, \] (2)

where \( a \) is maximum right or left lateral acceleration, and \( v \) is the vehicle’s velocity when the maximum lateral acceleration was observed. Maximum lateral acceleration is observed at a time interval of every \( T \) seconds of continuously recorded lateral acceleration.

Figure 1 illustrates the relationship between vehicle velocity (\( v \)) and estimated radius of curvature (\( R \)) for two different drivers. The upper and lower halves of each graph indicate the radii of curvature to the right and left, respectively, and the solid lines represent the minimum safe radii of road curvature, i.e., the maximum safe speed for that degree of road curvature. Each dot represents (\( v, R \)) at time intervals of \( T \). The dots outside solid lines indicate abrupt steering, whereas dots inside the solid lines indicate safe steering operation. Therefore, the aggressiveness of the steering behavior (\( f_s \)) of each driver can be determined by calculating the proportion of dots outside the solid lines in relation to the overall number of dots. The proportion of abrupt steering operations (6.1%) is smaller for the driver on the left in comparison to the driver on the right (26.5%), so we assume that the steering behavior of the driver on the left is less aggressive.

2.2 Acceleration Behavior

We assume that both rapid acceleration and excessive speed are indicators of aggressive acceleration behavior. The feature used to measure rapid acceleration, \( f_a \), is defined as initial acceleration when the driver begins moving from a complete stop. The feature used to measure excessive speed, \( f_v \), is defined as the preferred velocity of the driver when cruising (stable velocity...
without additional acceleration). Initial acceleration and preferred velocity are used as features to indicate the aggressiveness of acceleration behavior.

To evaluate values for initial acceleration and velocity without additional acceleration, we use a two-dimensional plane whose axes represent maximum longitudinal vehicle acceleration and vehicle velocity when the maximum acceleration was observed. Maximum longitudinal vehicle acceleration is selected at time interval $T$, which is determined by a preliminary experiment. Here, we are assuming that each driver has preferred cruising speeds and that maximum acceleration is almost inversely proportional to velocity, i.e., as velocity increases, acceleration decreases. The distribution of driving data in the two-dimensional plane is approximated with a line, and orthogonal linear regression \(^{(15)}\) is used to obtain two intercepts, one for each axis. As shown in Fig. 2, the intercept of the vertical axis ($y$-intercept) corresponds to initial acceleration when the driver accelerates from a stop, which is the acceleration rate the driver prefers when he or she begins moving. The intercept of the horizontal axis ($x$-intercept) corresponds to preferred velocity, which is the cruising velocity the driver prefers. Figure 2 shows the two-dimensional planes for two drivers. We can see that the driver on the left has a higher preferred cruising velocity, whereas the driver on the right accelerates more rapidly from a stop.

### 2.3 Deceleration Behavior

**We assume that deceleration behavior is aggressive if a driver brakes rapidly while driving. Rapid braking can be defined as braking which causes sharper deceleration than is considered to be comfortable for the occupants of the vehicle.** According to research done by the American Association of State Highway and Transportation Officials (AASHTO), in most cases a comfortable deceleration is less than 2.5 m/s\(^2\) (0.26 G) \(^{(16)}\). In our study, if deceleration exceeds 0.3 G it is assumed to be caused by rapid braking, and the frequency of such rapid braking operations is used as the feature indicating aggressive deceleration behavior ($f_{dc}$).

#### 2.4 Alternation between Acceleration and Deceleration

We assume that aggressive alternation between acceleration and deceleration can be represented by frequent alternation between depressing the gas and brake pedals, which may lead to unstable traveling velocities, acceleration, and jerk. Jerk at time point $t$, $\ddot{a}(t)$, is calculated as a dynamic feature of acceleration signals using linear regression:

$$\ddot{a}(t) = \frac{\sum_{k=1}^{K} k (a(t+k) - a(t-k))}{2 \sum_{k=1}^{K} k^2} \quad \ldots \ldots \ldots (3)$$

where $a(t)$ is longitudinal acceleration and $K$ is the parameter for controlling window length of the regression. Instability in traveling velocity, acceleration, and jerk can be described by their standard deviations. The standard deviations of velocity ($f_{cv}$), acceleration ($f_{ca}$), and jerk ($f_{cj}$), are used as features to indicate alternation between acceleration and deceleration.

### 3. Experiment

We conducted an experiment to evaluate the effectiveness of our proposed method at predicting aggressive driving behavior. The experiment had two parts: 1. Evaluate the extracted features representing aggressiveness for the four sub-behaviors; 2. Predict the overall aggressiveness of a driver’s behavior using Eq. (1), by multiple linear regression (MLR) or principal component regression (PCR).

#### 3.1 Driving Data used for Evaluation

The driving behavior signals used in our study were provided by a risk consulting company, and were collected using drive recorders mounted on vehicles owned by companies, with a sampling rate of 10 Hz. All of the vehicles used for data collection were equipped with the same type of drive recorder. These drive recorders had been in use by the risk consulting company for several years. The recorded signals included longitudinal and lateral acceleration, GPS data, and video to the front. Vehicle velocity was also calculated using GPS. Acceleration sensors were set on the floors of the vehicles to ensure they were level. However, the GPS data and video were not provided for privacy reasons. We used driving data collected from 78 drivers as they drove on city streets and highways from 2005 to 2006, for an average duration of about 105 minutes per driver. The driving behavior of each of the same 78 drivers was also evaluated by the risk consultants based on empirical criteria formulated by an expert who had been working for a...
Table 3. Distribution of empirical scores of risk consulting experts, from 1 (least aggressive) to 5 (most aggressive)

| Frequency (# of drivers) | 1 | 2 | 3 | 4 | 5 | Total (# of drivers) |
|--------------------------|---|---|---|---|---|----------------------|
| 5                        | 10| 23| 20| 50| 78|                      |

We calculated the Spearman’s rank correlation coefficient between the empirical aggressiveness score assigned to that driver by the risk consultants and the empirical scores of the risk consulting experts, from 1 (least aggressive) to 5 (most aggressive). Although details of the consultant’s evaluation criteria are not available to the public, aggressiveness scores based on the criteria have some correlation to the actual number of traffic accidents, according to the records of the risk consulting company. The risk consultants’ scores are based on a proprietary combination of empirical criteria, and the evaluation criteria are not available to the public. These empirical scores ranged from 1 to 5, with 1 indicating the least aggressive driving behavior, and 5 indicating the most aggressive driving behavior. The distribution of the risk consultants’ empirical scores for the 78 drivers are shown in Table 3. Drivers were evaluated once by one expert. We evaluated our proposed method by comparing our aggressiveness score for each driver with the empirical aggressiveness score assigned to that driver by the risk consultant.

3.2 Evaluation of Features used to Measure Aggressiveness

We calculated the Spearman’s rank correlation coefficients between the aggressiveness features of the vehicle operation behaviors and the empirical aggressiveness scores. Features of aggressiveness for steering and acceleration behavior were calculated at time interval $T$, which was set to be from 5 to 55 seconds independently. The results of a preliminary experiment using different values of $T$, and the correlation coefficients for $f_s$, $f_a$, and $f_v$, with a significance level of less than 0.05, are shown in Table 4. $T$ was not used for calculating $f_b$, $f_c$, $f_e$, or $f_j$, because we used all of the data to calculate these features. The correlation coefficients for $f_s$, $f_a$, $f_e$, and $f_j$ were 0.26, 0.33, 0.43, and 0.46, respectively. We then used these features to predict the aggressiveness of driving behavior using multiple linear regression. For $f_s$, $f_a$, and $f_e$, the features with $T$, which results in the maximum correlation coefficients, were employed. The relationship between the empirical scores of the risk consultants and each of our extracted aggressiveness features are shown in Figs. 3–9.

We found that, compared with the features of other driving behaviors, abrupt steering ($f_j$) had a relatively low correlation coefficient (about 0.2) in relation to the empirical aggressiveness scores of the risk consulting experts. This may be because not much driving around curves was captured in the recorded data, however this is difficult to confirm since we did not have access to the recorded video data. On the other hand, the features of acceleration behavior ($f_s$), i.e., acceleration from a stop, and alternation behavior ($f_a$), i.e., standard deviation of jerk, showed relatively high correlation coefficients (about 0.5) in relation to the consultants’ aggressiveness scores.

3.3 PCA for Features

Correlation coefficients of the relationships among features of the various driving behaviors is shown in Table 5. We can see that these features are not completely independent of each other, and that some of the features even have relatively strong correlations. The correlation coefficient between $f_a$ (proportion of abrupt steering operations) and $f_j$ (driver’s preferred speed) is 0.57, which can be understood if we assume that driving at higher speeds results in more abrupt steering behavior. $f_a$ (acceleration from a stop) is strongly associated with both $f_e$ (standard deviation of longitudinal acceleration) and $f_j$ (standard deviation of jerk), with correlation coefficients of 0.67 and 0.55, respectively. This seems reasonable, because rapid acceleration may result in unstable acceleration and jerk. For the same possible reason, $f_b$ (frequency of rapid braking) is strongly associated with $f_e$, $f_a$, and $f_j$, with covariances of 0.50, 0.79, and 0.57, respectively. Furthermore, it is not difficult to understand the strong correlations that also exist between

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The aggressiveness of each driver’s behavior was predicted using MLR and PCR. However, further study is needed to interpret the precise meaning of each principal component. Therefore, we apply PCA to the features of each behavior prior to performing linear regression.

Contribution ratios of each principal component and their cumulative curves are shown in Fig. 10. These principal components are ordered according to their contribution ratios, i.e., the principal component with the maximum contribution ratio corresponds to the first principal component. After analyzing the principal components, we found that the first principal component seemed to be mainly related to the riskiness of acceleration and deceleration behavior, and the second principal component seemed to represent the driver’s preferred velocity as well as the riskiness of steering behavior. However, further study is needed to interpret the precise meaning of each principal component.

### 3.4 Aggressiveness Prediction using MLR and PCR

The aggressiveness of each driver’s behavior was predicted using Eq. (1), employing both multiple linear regression.
Table 6. Feature sets used for driving aggressiveness prediction and their correlation coefficients, with a significance level less than 0.01

| Feature set | Contribution ratio in total variance [%] | Correlation coefficient |
|-------------|-----------------------------------------|------------------------|
| | | |
| MLR | ALL | \( \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{5}, \frac{1}{6}, \frac{1}{7}, \frac{1}{8} \) | 100 | 0.64 |
| | | 2nd and 3rd principal components | 21.7 | 0.38 |
| | | 1st–3rd principal components | 83.3 | 0.67 |
| | | 1st–4th, 6th principal components | 91.5 | 0.74 |
| | | 1st–4th, 6th, 7th principal components | 93.4 | 0.67 |
| | | 1st–7th principal components | 94.5 | 0.66 |
| | | 100 | 0.64 |
| PCR | | | |

Fig. 11. Correlation between experts’ scores and automated aggressiveness scores, using MLR with all features (ALL). Correlation coefficient \( r = 0.64 \)

Fig. 12. Correlation between experts’ scores and automated aggressiveness scores, using PCR with first four principal components (\( P_4 \)). Correlation coefficient \( r = 0.74 \)

Table 7. Regression coefficients for ALL and \( P_4 \)

| | | | | | | | |
|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| | | | | | | | |
| ALL | \( \alpha_0 \) | 3.51 | | \( \alpha_2 \) | 0.50 | | \( \alpha_3 \) | 0.25 | | \( \alpha_4 \) | 0.21 | | \( \alpha_5 \) | -0.35 | | \( \alpha_6 \) | 0.19 | | \( \alpha_7 \) | 0.48 | | \( \alpha_8 \) | 0.33 |
| \( P_4 \) | \( \alpha_0 \) | 3.51 | | \( \alpha_2 \) | 0.23 | | \( \alpha_3 \) | 0.37 | | \( \alpha_4 \) | 0.49 | | \( \alpha_5 \) | 0.20 | | \( \alpha_6 \) | - - | | \( \alpha_7 \) | - - | | \( \alpha_8 \) | - - |

(MLR) and principal component regression (PCR). We employed the leave-one-out method, i.e., the driving data from 77 drivers was used to estimate the regression coefficients for the remaining (target) driver. We used 128 kinds of feature sets (one for MLR and 127 combinations for PCR) to estimate the aggressiveness of the drivers’ behavior. To evaluate the results of each feature set, we calculated the Spearman’s rank correlation coefficient and root mean square error (RMSE) between the empirical scores assigned by the risk consulting experts and the aggressiveness scores assigned using our method.

3.4.1 Correlation Coefficient Table 6 shows feature sets used for driving aggressiveness prediction and their rank correlation coefficients between the predicted aggressiveness scores using our proposed method and the empirical scores assigned by risk consulting experts. ALL used all of the features extracted from the driving behaviors to estimate regression coefficients directly using MLR. We used \( P_1 \) to indicate the feature sets for PCR which employed combinations of \( i \) principal components to estimate regression coefficients. For those feature sets using the same number of principal components, only the one with highest correlation coefficient is listed in Table 6.

We can see in Table 6 that correlation coefficients vary from 0.38 to 0.74, and that the highest correlation coefficient was obtained using feature set \( P_4 \), which employed the first four principal components. All seven principal components were employed in \( P_7 \), with a resulting correlation coefficient of 0.64, which was the same as ALL.

Results using ALL (MCR) and \( P_4 \) (PCR) are shown in Figs. 11 and 12, respectively. In both these figures, correlations between the experts’ scores and our predicted aggressiveness scores can be observed, with correlation coefficients of 0.64 (ALL) and 0.74 (\( P_4 \)), respectively. However, a more obvious descending ladder-like shape from left to right was obtained by PCR showing higher correlation than MLR. Regression coefficients for ALL and \( P_4 \) are shown in Table 7. Since we predicted the aggressiveness scores of 78 drivers using the leave-one-out method, there were 78 sets of regression coefficients \( \{ \alpha_i \} \), and it is difficult to show them all. Instead, Table 7 shows \( \alpha_1 \) calculated using the data of all 78 drivers. We found that when we employed ALL, regression coefficient \( \alpha_1 \), which corresponds to risky frequency of braking operations, became negative. This is difficult to understand, but it may have been caused by multi-collinearity.

3.4.2 Prediction Error Figure 13 shows the root-mean-square error (RMSE) of our predicted aggressiveness scores in comparison to the risk consultants’ scores. RANDOM represents the RMSE for randomly selected scores from 1 to 5. The smallest RMSE of 0.82 was obtained for \( P_4 \), with RMSE increasing to 0.99 for ALL and \( P_7 \), and 1.92 for RANDOM.

4. Conclusion A technique for measuring the aggressiveness of driving behavior was proposed in this study, based on the use of driving behavior signals and principal component regression. We assumed that aggressiveness could be measured by analyzing four types of driving behavior, i.e., steering behavior, acceleration behavior, deceleration behavior, and alternation between acceleration and deceleration. The overall
aggressiveness of a driver’s behavior was measured by extracting the aggressiveness features from these behaviors and then integrating these features using MLR or PCR. We used the proposed method to measure the aggressiveness of 78 drivers of company-owned vehicles, using driving data collected with drive recorders during real-world driving. We then evaluated its performance by comparing our aggressiveness scores with the aggressiveness scores assigned to the same 78 drivers by risk consulting experts. Experimental results showed that our multiple linear regression model achieved a performance correlation coefficient of 0.74 in relation to the empirical evaluations of the risk consulting experts. By applying PCA to the feature sets, prediction performance was improved and a correlation coefficient of 0.74 was obtained.

The next step in our work is to investigate more effective features for detecting abrupt steering operation. We would also like to develop and employ additional aggressiveness features based on other driving behaviors, in order to better detect aggressive driving behavior. According to research done by the NHTSA, aggressive drivers are more likely to tailgate, to make improper and unsafe lane changes, and to make emotional hand and facial gestures\(^{190}\). The increased presence of various types of sensors, such as cameras and distance sensors, may make it easier to capture these types of driving behaviors in recorded data, which could assist in improving automated detection of aggressive driving behavior. Aggressive driving behavior has also been the focus of research in the field of psychology for several decades, and many significant findings have been reported\(^{199–201}\), so we may be able to improve our ability to detect aggressive driving behavior by combining the observation of driving signals with psychological models.

Acknowledgment

This work was partially supported by Grant-in-Aid for Scientific Research (C) No. 24500200, and by the Core Research of Evolutional Science and Technology (CREST) Program of the Japan Science and Technology Agency (JST). We would also like to thank Tokio Marine & Nichido Risk Consulting Co., Ltd. for providing drive recorder and risk evaluation data.

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