ABSTRACT

We propose a driver risk evaluation method based on the analysis of driving data captured with drive recorders. To evaluate the acceleration behavior of each driver we plot the maximum acceleration per minute to velocity on a two-dimensional plane and approximate the distribution by linear regression. We assume that the higher the y-intercept of the line, the quicker the driver accelerates from a stop, and the higher the x-intercept, the higher the preferred speed of travel. To evaluate deceleration behavior, brake pedal operation patterns are classified into four types, based on how the brake is depressed and released. We evaluate deceleration risk levels based on these four braking pattern categories. Steering behavior is evaluated based on the relationship between the radius of road curvature and road design speed as defined in the road construction ordinance. Some correlation is observed between our evaluation results and those manually scored by risk consultants.

Index Terms—Drive recorder, driver risk evaluation, acceleration, deceleration, steering

1. INTRODUCTION

Drive recorders, also known as event data recorders (EDRs) are widely used to monitor commercial fleets, such as taxis, trucks and buses [1,2]. For example, more than 50% of taxis in Japan have drive recorders for safety and security reasons. A drive recorder is triggered when an event such as sudden deceleration is detected, and then records signals such as acceleration, GPS, velocity, and video images. It functions as a witness to traffic accidents. Recently, they are also used to promote safe driving and eco-driving. The drive recorder data are analyzed by risk consulting experts and each driver is evaluated according to the analyzed data. The driver evaluation results, such as the frequency of rough braking actions, are reported to the fleet company, and the driver is given feedback to reduce risky driving behavior. It has been reported that the use of drive recorders and risk consulting has resulted in a 20 to 80% reduction in the number of traffic accidents [2]. However, since these consulting methods are empirically implemented by risk consulting experts, the manual process can be time-consuming and costly. Therefore, an automatic and efficient driver evaluation method is needed.

In this paper, we propose a new method for scoring driver risk based on pedal-pressing and steering behavior for automatic driver risk evaluation. Longitudinal and lateral acceleration and velocity signals captured with drive recorders are used for the analysis.

2. DRIVER EVALUATION METHOD

2.1. Evaluation of Acceleration Behavior

Driver acceleration behavior is evaluated in a two-dimensional plane using maximum longitudinal vehicle acceleration per minute and vehicle velocity when the maximum acceleration is observed. Figure 1 shows examples of the two-dimensional representation of the driving data of four drivers. The distribution is approximated with a line by linear regression. We assume the y-intercept of the line corresponds to the initial acceleration when the driver starts moving, and the x-intercept of the line corresponds to the velocity the driver prefers (velocity without additional acceleration). The higher the y-intercept on the graph, the quicker the driver accelerates from a stop. On the other hand, the higher the x-intercept, the higher the preferred speed of travel of the driver. So drivers whose driving is represented by a graph like driver 1 are the safest, and those whose driving is represented by a graph like driver 4 are the least safe, because type-4 drivers have high x- and y-intercepts. Type-2 drivers accelerate from a stop moderately, but prefer to travel at higher speeds, while type-3 drivers accelerate rapidly, but travel at moderate speeds.

Using drive recorder data provided by a risk consulting company, we analyzed the acceleration behavior of 392 drivers. The drive recorder data included longitudinal acceleration signals measured with a gyroscope and GPS velocities recorded once a minute. The distribution of x- and y-intercepts of the drivers is shown in Fig. 2.
By choosing certain thresholds for x- and y-intercepts, e.g., 0.22G and 95 km/h, respectively, drivers can be classified into one of the four types shown in Fig. 1.

Figure 3 shows the relationship between the x-intercepts of the regression line and evaluation scores from A to E of risk consulting experts, with A representing the lowest risk and E the highest risk, while Fig. 4 shows the relationship between the y-intercepts and risk consulting ratings. We can see some correlation between the x-intercept and risk consultant scores and a relatively high correlation between the y-intercept and their scores. Risk consultants use not only acceleration behavior, but also other factors such as braking, steering, u-turns, and so on. They also review videos taken by the cameras of drive recorders. However, this manual process can be time-consuming and costly. We expect that our evaluation measure would show a higher correlation to the risk consultants’ scores if we also took other driving behavior into account.

2.2. Evaluation of Deceleration Behavior

To evaluate driver deceleration behavior, we first categorized the braking events (which exceeded -0.3G) into four categories. We ranked braking patterns from A to D, with A representing the most risky and D the least risky. Please note that conventional drive recorders assume these events are equally dangerous.

Each braking event was represented as a 6.4-second segment of acceleration signal which was extracted from the original signal recorded by drive recorders. The length of the segment was designed to be matched to the intervals of depressing and releasing the brake pedal [3]. To classify the brake pedal patterns based on the braking situation, we used an LBG algorithm [4] to cluster the segment data. An example of braking pattern classification is shown in Fig. 5.
The following four patterns represent different ways of braking in response to different traffic situations.

A. **Sudden braking**: driver depressed and released the brake sharply, such as when the forward vehicle unexpectedly decelerated.

B. **Intensive and long braking**: driver drove at high speed and then rapidly and heavily decelerated, and then released the pedal gradually.

C. **Situation-aware braking**: driver was aware of the traffic situation in advance, decelerated gradually, and then quickly removed his foot from the brake.

D. **Moderate braking**: driver decelerated slowly and then drove at a lower rate or stopped, depressing the pedal gradually and then releasing it gradually.

Most of the braking patterns which fall into the A category involve emergency braking, e.g., a driver had to brake suddenly to avoid a collision because the car in front decelerated rapidly. In such cases, the driver may have failed to anticipate this possibility, and was driving with a short inter-vehicle distance. In contrast, the D braking pattern is less dangerous, e.g., that of a driver who was aware of a red light far enough in advance of the intersection, and decelerated gradually to a stop. Using these four braking patterns, the deceleration behavior of drivers can be evaluated according to various criteria as follows.

**Criterion 1. Proportion of sudden braking**: Among braking patterns A-D, rapidly depressed patterns (A and B) are considered more dangerous. The proportion of the sum of patterns A and B to the whole was computed individually. A high percentage of patterns A and B (like driver 6 in Fig. 6) means the driver tends to engage in risky braking. On the contrary, we assume that drivers with a low percentage of patterns A and B (like driver 5 in Fig. 6) tend to drive more safely.

**Criterion 2. Uniqueness**: Within each cluster of the four patterns A-D, the average Euclidean distance between the general braking pattern and segment data that belong to the target cluster was calculated. The general braking pattern is a centroid, which was obtained by applying the LBG algorithm to data from all the drivers. We assumed the distance indicates the degree of uniqueness of each braking pattern. A driver with a large distance is considered an outlier, while a small distance from the centroid indicates a common driving pattern.

**Criterion 3. Unsteadiness**: This is defined as variability of the driving behavior. The sum of the variance of distances in each cluster was calculated. Drivers who had a large variance in their braking patterns were said to exhibit unstable braking behavior, while drivers who had little variance were considered to have stable braking behavior.

We applied these three criteria to 35 drivers. However, the average of the three scores of each driver did not show significant correlation to the scores of risk consultants. This low correlation to the scores given by risk consultants could be because they considered other factors such as acceleration, steering, etc., and that they did not classify the braking events precisely.

**2.3. Evaluation of Steering Behavior**

The minimum radius of road curvature depends on road design speed, which is specified in the road construction ordinance No. 15 [5]. Table 1 shows the relationship between the radius of curvature and road design speed. We approximate vehicle motion while steering as a circular motion and estimate the radius of the curvature of vehicle trajectory $R$ [m] based on a circular motion equation:

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

where $a$ [m/s$^2$] is right or left lateral acceleration and $v$ [m/s] is vehicle velocity. We assume that steering with a smaller radius of curvature than that of Table 1 is risky [6].
Table 1: Relationship between road design speed and minimum radius of curvature defined in Japanese road construction ordinance.

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<tr>
<th>Road design speed [km/h]</th>
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Fig. 7: Examples of steering behavior for two different drivers.

We evaluated the steering behaviors of 203 drivers. The drivers drove more than 25 hours in total. The radius of curvature was estimated from acceleration and velocity pairs and plotted on a two-dimensional space using velocity and radius of curvature. The risk level of the steering behavior of each driver was evaluated from the data plots. We assumed the plots exceeding the threshold line derived from Table 1 to be risky steering operations.

Figure 7 shows examples of the data plots for two drivers. The upper and lower halves illustrate the steering operations to the left and right, respectively. Distributions of the dots on the left and right halves are nearly symmetrical and differ from driver to driver. The percentage of risky steering operations of drivers 7 and 8 was 0.2% and 15%, respectively. We assume that steering behavior of driver 7 is safer than that of driver 8.

Figure 8 shows the relationship between the proportion of risky steering and the number of drivers who were rated from A to E by risk consultants. We can see a correlation between them.

3. CONCLUSION AND FUTURE WORK

In this paper, we proposed a driver risk evaluation method based on the analysis of driver’s acceleration, deceleration, and steering behavior. We could observe some correlation between our driver evaluation results and ratings manually assigned by risk consulting experts with regards to acceleration and steering operation.

In future research, we plan to integrate our three risk evaluation methods (analysis of acceleration, deceleration, and steering behavior), and to also incorporate other driving behavior factors into our analysis. Further, we need to verify the accuracy of our driver evaluation method by examining more thoroughly the correlation between our risk predictions and those of risk consulting experts.

4. ACKNOWLEDGEMENTS

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5. REFERENCES