# Self-Coaching System Based on Recorded Driving Data: Learning From One's Experiences

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***Abstract*—This paper describes the development of a self-coaching system to improve driving behavior by allowing drivers to review a record of their own driving activity. By employing stochastic driver-behavior modeling, the proposed system is able to detect a wide range of potentially hazardous situations, which conventional event data recorders are not able to capture, including those involving latent risks, of which drivers themselves are unaware. By utilizing these automatically detected hazardous situations, our web-based system offers a user-friendly interface for drivers to navigate and review each hazardous situation in detail (e.g., driving scenes are categorized into different types of hazardous situations and are displayed with corresponding multimodal driving signals). Furthermore, the system provides feedback on each risky driving behavior and suggests how users can safely respond to such situations. The proposed system establishes a cooperative relationship between the driver, the vehicle, and the driving environment, leading to the development of the next generation of safety systems and paving the way for an alternative form of driving education that could further reduce the number of fatal accidents. The system's potential benefits are demonstrated through preliminary extensive evaluation of an on-road experiment, showing that safe-driving behavior can be significantly improved when drivers use the proposed system.**

***Index Terms*—Detection of risky driving, diagnosis and feedback system, driver coaching, potentially hazardous situation, self-directed learning.**

## I. Introduction

IN RECENT years, in addition to passive safety systems (e.g., airbags, seat belts, and laminated glass), active safety systems such as assisted braking systems, adaptive cruise control, and intelligent speed adaptation, have played an increasing role in reducing the number of fatal traffic accidents [1]. In general, active safety systems can be operated manually by a driver or automatically by a computer system in response to sensory data that provide information regarding the vehicle's state. Nevertheless, as these active systems become more advanced and sophisticated, several researchers and developers have raised questions about their limitations (e.g., application specific), their functionality (e.g., when the system should intervene), and their impact on drivers (e.g., overreliance). To overcome such problems and to further reduce the number of future accidents, we believe that cooperative safety systems, which take into account driver behavior, vehicle status, and driving environment as one whole system are essential for developing more effective safety systems. Our objective in this research is to develop effective ways of enhancing cooperative safety systems by focusing on the relationship between the driver, the vehicle, and the driving environment.

Event data recorders (EDRs) have been used to capture driving data, which are generally video and acceleration signals in real-world driving environments [2]. The primary use of EDR data is as evidence of what actually occurred during a traffic accident. These data can be analyzed in a similar manner to the data from a black box in an airplane. Furthermore, according to a risk consulting company, the number of traffic accidents was reduced by more than 30% when vehicles were equipped with EDRs and safety guidance was provided to drivers using their own recorded driving behavior [3]. Motivated by this insight, and extended from our previous work [4], [5], we present the development of a next-generation EDR, which is capable of detecting a wide range of potentially hazardous situations and risky driving behavior that would not be captured by conventional EDRs. We also show how these data can be used to subsequently instruct drivers on how they can improve their driving by adopting safer driving behavior.

The proposed system employs a data-centric approach to record, analyze, and retrieve large amounts of observations from real-world driving signals [6]. In addition to explicitly risky incidents that would be normally captured by conventional EDRs (e.g., sudden deceleration) [7], the proposed system is able to capture potentially risky incidents by employing advanced sensory systems and stochastic driver behavior models. Driver-behavior models based on Gaussian mixture models (GMMs) representing safe and risky driving behavior were exploited to automatically detect risky driving behavior from the recorded driving data. Finally, a web-based driving diagnosis and feedback system was developed. The system allows a

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user to browse through their own detected hazardous situations, which are categorized by different types of risky behaviors, along with the corresponding driving signals. Subsequently, the system explains why the driving behavior detected in that situation is considered unsafe and makes a suggestion on how it can be improved.

Experimental evaluations were conducted to verify the usefulness of our system in reducing the number of potentially hazardous situations caused by unsafe driving behavior. A total of 33 drivers, including six professional drivers, participated in our study. Experimental results showed a significant reduction in the number of detected hazardous situations for the normal drivers who used our system, compared with those who did not use our system. Preliminary analysis was also performed to validate the effectiveness of the proposed system on improving long-term behavior, as well as evaluating the subjective opinion of drivers toward the system. These results showed that a driver's ability to perceive and understand hazardous situations, which are usually obtained through driving experience, can be enhanced by coaching them with their own driving data.

This paper is organized as follows. In the next section, we briefly discuss the limitations of conventional EDRs and traditional driving improvement methods. In Section III, we discuss our method of collecting on-the-road driving data. Then, in Section IV, the algorithm for detecting hazardous situations is discussed. Section V describes our web-based automatic diagnosis and self-review system, including experimental evaluation and analysis. Finally, this paper is concluded in Section VI.

## II. Background and Motivation

### A. Limitations of Conventional EDRs

In the past decade, to study driving behavior in a realistic driving environment and perform accident analysis, EDRs have been installed in automobiles to record vehicle information and driving scenes related to collisions and near collisions [2]. Conventional EDRs are triggered by sudden changes in velocity (e.g., extreme acceleration or deceleration rates), which usually occur as a result of driver responses to hazardous situations, and then continuously record data for some time thereafter. Some EDRs may also record a few minutes of buffering data before they are activated. However, in addition to these explicitly hazardous situations, which are able to be perceived and responded to by drivers, there are many other latent hazardous situations that are not recorded by EDRs (e.g., situations where drivers do not take evasive action or do not alter their driving behavior in response to hazardous situations, due to carelessness or inattention). In some cases, collisions or near collisions are avoided only because other parties react in time to prevent them (e.g., when a pedestrian stops before entering the roadway). Fig. 1 shows which hypothetical-hazardous situation detection zones conventional EDRs are able (and unable) to capture. Detecting and recording these latent hazardous situations would be useful for improving overall traffic safety since these recurring risky situations can cause serious accidents at any time. Table I lists the different types of hazardous situations that may lead to collisions or near collisions (based on the analysis of the data in our corpus). Conventional EDRs may be able to record situations 1–3 on the list in Table I. Some advanced sensory systems may be able to record up to the first seven types of hazardous situations listed, but none are able to capture all of the events. Some EDRs are designed to continuously record all driving data, i.e., continuous data recorders (CDRs). However, most of the recorded data are not useful, and the processing cost is too high to fully exploit all the data. Therefore, we aim to develop a next-generation EDR that efficiently and automatically detects all the hazardous situations listed in Table I.

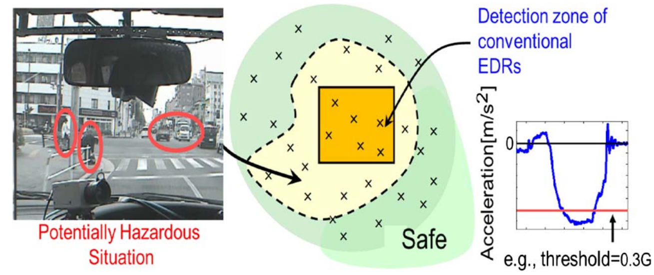



Fig. 1. Detection zone of conventional EDRs in relation to all potentially hazardous situations.

TABLE I
DIFFERENT TYPES OF HAZARDOUS SITUATIONS CAPTURED BY CDR

| |
|---|
| 1) Sudden Deceleration |
| 2) Sudden Acceleration |
| 3) Risky Steering |
| 4) Excessive Speed |
| 5) Ignoring a Traffic Light |
| 6) Ignoring a Stop Sign |
| 7) Insufficient Following Distance |
| 8) Risky Obstacle Avoidance |
| 9) Risky Behavior at a Poor-Visibility Intersection |

### B. Limitations of Driving Improvement Methodologies

Although there are several current efforts in the field of driver education that attempt to reduce traffic accidents, particularly for novice drivers (such as in-class/in-vehicle instruction, interactive, home-based programs, and online courses), their effectiveness is restricted by the limited amount of actual driving involved and the absence of feedback that takes into account the individual driving characteristics of each driver [8]. Drivers gain more driving experience and skill at perceiving hazardous situations when they are exposed to a variety of real-world driving situations. Furthermore, safe driving habits may not be implanted in novice drivers due to lack of proper instruction being given, and it is not practical to have a driving instructor with novice drivers at all times. In addition, driver's personality and individual driving characteristics have an indirect effect on risky driving behavior and on the risk of being involved in an accident, due to the individual's unique perception and appraisal of the driving environment [9]. Therefore, an integrated system that allows drivers to review their own recorded driving experiences, points out risky driving behavior, and instructs them on how to improve their behavior will truly help them

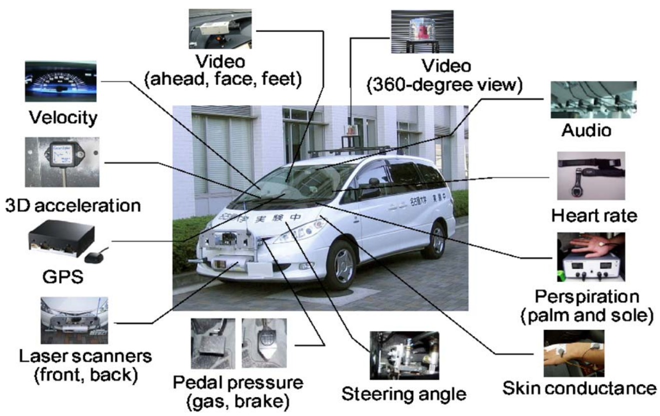



Fig. 2. Instrumented vehicle equipped with various types of sensory systems.

improve their driving skills and nurture safe driving habits. As a result, this will reduce the overall number of accidents and their often tragic consequences.

## III. Large-Scale On-Road Driving Database

To analyze driver behavior and develop our system, we used a large amount of real-world observations that were synchronously collected using an instrumented vehicle, as shown in Fig. 2. The vehicle is equipped with a wide range of sensors and data recording systems. The rich multimodal data contains 12-channel audio, four-channel video (capturing the front-view scene, as well as the driver's face and feet), GPS information, driving behavior signals (including gas and brake pedal pressure, steering angle, following distance, and vehicle velocity), physiological signals (including the driver's heart rate, skin conductance, and emotion-based sweating on the palms and soles), etc. In particular, the steering angle is obtained using a potentiometer. The brake and gas pedal pressures are obtained using pressure sensors. Vehicle velocity is measured using the output from a pulse generator. Following distance from a lead vehicle is acquired using two types of distance sensors and a laser scanner mounted on the front of the vehicle. More details about the vehicle setup can be found in [10] and [11]. Each driver drove the instrumented vehicle on the same route around the Nagoya, Japan, area in a variety of environments and actual traffic conditions. All the drivers performed particular secondary tasks while driving at the same locations, such as reading signs and billboards aloud, listening to and repeating alphanumeric strings, following the instructions of a human navigator, and interacting with a spoken dialog music retrieval system. The resulting driving corpus was considered to be one of the world's largest on-the-road driving databases at the time this paper was written, with more than 550 participants taking part in the project.

## IV. Detection of Hazardous Situations

In this section, we discuss the developmental framework for detecting potentially hazardous situations and risky driving behavior from the recorded driving data. Hidden hazardous situations that may not be captured by conventional EDRs include signals turning yellow, crossing vehicles at intersections, and pedestrians making ambiguous movements at crosswalks. For the purpose of data analysis and for training the driver-behavior model, a human annotator watched all the video obtained from the front-view camera and manually identified hazardous situations. Then, the annotator observed whether the driver anticipated the possibility of the event and took appropriate action, based on a manual of potential danger analysis in different driving situations [12], [13]. The manual was developed to provide guidance regarding a variety of hazardous situations, based on traffic psychology and Japanese driving rules. It suggests appropriate driver responses for safely handling each situation.[1] For example, potentially hazardous situations could exist when a driver is turning left at an intersection with a traffic light, both before and during the left turn, as described in more detail in Fig. 3. In this paper, we define a potentially hazardous situation as one in which a driver fails to take appropriate action as described in the manual.

### A. System Development

Hazardous situations of types 1–7 (Table I) can be straightforwardly detected using a rule-based approach or by thresholding the observed driving data (e.g., steering angle, deceleration, velocity, and following distance), together with vehicle position within the driving environment (e.g., GPS information), against an empirical predefined value. In this paper, our methodology to detect different types of hazardous situations is described as follows:

*1) Sudden Deceleration, Sudden Acceleration, and Risky Steering:* These incidents can be detected by thresholding the acceleration value, deceleration value, and steering-wheel angle, respectively, in a similar manner as in conventional EDRs. For instance, a sudden-deceleration incident occurs when longitudinal acceleration is lower than $-0.45$ G.

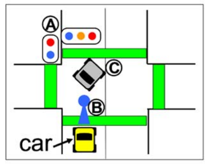
*2) Exceeding the Speed Limit:* This incident is detected by comparing the enforced speed limit information of a section of the route[2] with the observed velocity of the vehicle. The positions of a vehicle in each speed-limit zone is obtained using GPS information, and then, the corresponding enforced speed limit is used to compare with the observed vehicle speed. Note that the current system does not consider noncompliance with temporary speed limits in place due to unusual weather conditions, construction zones, etc.

*3) Ignoring a Traffic Light:* This incident is detected by manually observing a traffic signal changing to yellow (by monitoring video from the front-viewed camera) and then calculating whether the driver entered the intersection in error, instead of stopping the vehicle (i.e., exceeding the limit of a

[1]Note that the guidance used in this study was developed specifically for driving behavior in Japan. As driving behavior in different countries is characterized by diverse rules and cultures (e.g., driving direction and traffic control at intersections), a customized guidance is recommended for particular traffic regulations of each country.

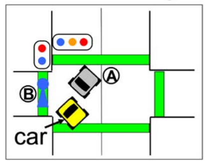
[2]In this paper, information on each speed-limit zone was obtained in advance. In the future, such information could be obtained by robust traffic sign detection and advanced GPS information.

● Before entering an intersection




| Possible hazardous situations | Appropriate driver responses |
|---|---|
| A. The signal turns yellow | Stop before the line |
| B. There are pedestrians | Stop or go slowly |
| C. There is an oncoming car turning right | Stop or go slowly |

● While turning left at an intersection with a signal




| Possible hazardous situations | Appropriate driver responses |
|---|---|
| | Go slowly |
| A. There is an oncoming car turning right | Stop or go slowly |
| B. There are pedestrians | Stop or go slowly |

Fig. 3. Potentially hazardous situations while turning left at an intersection with traffic lights and corresponding appropriate/safe driver responses.

hypothetical "dilemma zone" for situations which are difficult for drivers to judge [14]).

*4) Ignoring a Stop Sign:* This incident is detected by using GPS information to locate the intersections with stop signs and then measuring vehicle velocity to determine whether the driver stopped.

*5) Insufficient Following Distance:* This incident is detected by thresholding the calculated time to collision (TTC, i.e., the time required for two vehicles to collide if they continue at their present speed on the same path [15]). We use a laser scanner to capture the distance to the lead vehicle. A threshold of 1.7-s TTC was applied in this study. Instead of measuring relative speed directly, we use the regression coefficient of the following distance in an 800-ms window to represent relative speed.

However, to automatically detect potential risk in cases involving driving through an uncontrolled intersection (i.e., one with no traffic lights or signs) or during obstacle avoidance (situations 8 and 9 from Table I, respectively), driver-behavior models are required to decide if risky driving behavior is present. Stochastic modeling frameworks (e.g., hidden Markov model, GMM) have shown great promise in capturing meaningful driving characteristics in several studies [6], [16], [17]. In the next section, we introduce GMM-based driver-behavior modeling, which can be employed for both detection and regression problems.

## B. GMM-Based Driver-Behavior Model

In the GMM [18], we assume that $K$ latent (hidden) components with different characteristics and corresponding parameters ($\theta_k$) underlie the observed data $O = \{o_i\}_{i=1}^N$. The observed data are generated from a mixture of these multiple components. In particular, the total amount of data generated by component $k$ is defined by its mixing probability $\pi_k$. The probability density function of $O$ given by a GMM with parameters $\Theta = \{\theta_k\}_{k=1}^K$ is given as

$$p(O|\Theta) = \prod_{i=1}^{N}\sum_{k=1}^{K}\pi_k p(o_i|\theta_k) \tag{1}$$

where $\theta_k = \{\mu_k, \Sigma_k\}$ is a unimodal Gaussian (Normal) distribution with a mean vector $\mu_k$ and a covariance matrix $\Sigma_k$, with a constraint of $\sum \pi_k = 1$, $\pi_k > 0$. The most practical and powerful method for obtaining estimate of the mixture parameters is the expectation-maximization algorithm.

*1) Mixture Model Regression:* The GMM can be exploited for a regression problem by assuming that an observation consists of both input stimuli $X = \{x_i\}_{i=1}^N$ (independent variables) and output responses $Y = \{y_i\}_{i=1}^N$ (dependent variables), i.e., $o_i = \{x_i, y_i\}$. Therefore, the GMM's parameters can be expressed as

$$\mu = \begin{bmatrix}\mu_x \\ \mu_y\end{bmatrix} \quad \Sigma = \begin{bmatrix}\Sigma_x & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_y\end{bmatrix} \text{ for each } k \text{ component.}$$

That is, mean vector $\mu$ is a concatenation of a mean vector of the input variables and a mean of the response variables. Similarly, the covariance matrix $\Sigma$ is composed of the autocovariance ($\Sigma_x$ and $\Sigma_y$) and cross-covariance ($\Sigma_{xy}$ and $\Sigma_{yx}$) matrices of these two variable sets. Subsequently, given a new set of stimuli $x_{\text{new}}$, the corresponding responses can be predicted via the conditional expectation of each component $E(Y|x_{\text{new}}, \theta_k)$, where

$$E[Y|x_{\text{new}}, \theta_k] = \mu_y + \Sigma_{yx}\Sigma_x^{-1}(x_{\text{new}} - \mu_x). \tag{2}$$

Finally, the predicted responses $y_{\text{pred}}$, given $x_{\text{new}}$ and a number of Gaussian components, can be computed as

$$y_{\text{pred}} = \sum_{k=1}^{K} h_k(x_{\text{new}})E[Y|x_{\text{new}}, \theta_k] \tag{3}$$

where $h_k(x_t)$ is a posterior probability that $x_t$ belongs to the $k$th component as

$$h_k(x_t) = \frac{\pi_k p(x_t|\theta_k)}{\sum_{j=1}^{K}\pi_j p(x_t|\theta_j)}, \quad 1 \le k \le K \tag{4}$$

where $p(x_t|\theta_k)$ is the marginal probability of the observed parameter $x_t$ generated by the $k$th Gaussian component.

*2) Pedal Prediction:* The GMM-based driver-behavior modeling was then applied in [17] and [19] to generate the car-following patterns of drivers. The GMM-based driver-behavior model represents patterns of pedal operation corresponding to the observed vehicle velocity and following distance. The underlying motivation of this modeling framework is

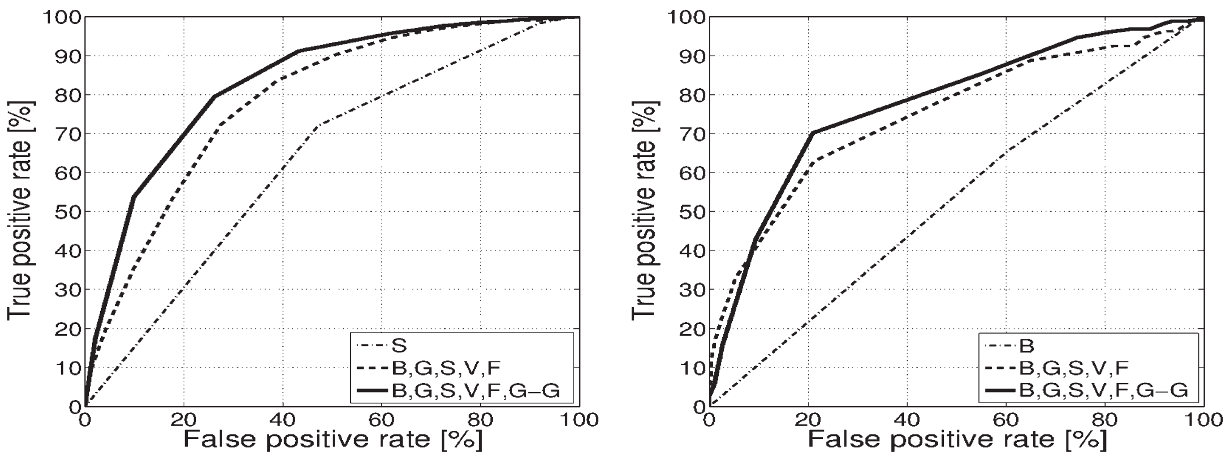



Fig. 4. ROC curves of risky driving detection performance (left) for obstacle avoidance and (right) for going straight through an intersection with no traffic light, employing different sets of observations (i.e., $O = S$ or $B$, $O = [B, G, S, V, F]^T$, and $O = [B, G, S, V, F, G - \hat{G}]^T$).

that, as a driver determines gas and brake pedal operation in response to the stimuli of vehicle velocity and following distance, accordingly, such patterns can be modeled by a joint distribution of all correlated parameters.

To model the gas-pedal pattern, an observed feature vector at time $t$, i.e., $x_t$, consists of vehicle velocity $V_t$, following distance $F_t$, and gas pedal pattern $G_t$ with their first- $\Delta$ and second-order $\Delta^2$ time derivatives as

$$x_t = [V_t, \Delta V_t, \Delta^2 V_t, F_t, \Delta F_t, \Delta^2 F_t, G_t, \Delta G_t, \Delta^2 G_t]^T \quad (5)$$

where the $\Delta(\cdot)$ operator of a parameter is defined as

$$\Delta V_t = V_t - \frac{\sum_{l=1}^{L} l \cdot V_{t-l}}{\sum_{l=1}^{L} l} \quad (6)$$

where $L$ is a window length (e.g., 0.8 s). Here, the driver's response parameter $Y$ is the future pedal operation $G_{t+\tau}$, where $\tau$ is an amount of prediction time (e.g., 0.5 s). Therefore, the observed feature vector $o_t$ can be defined as

$$o_t = \left[ x_t^T \quad G_{t+\tau} \right]^T. \quad (7)$$

Finally, the predicted pedal operation $\hat{G}_{t+\tau}$ can be calculated by using (3).

### C. Risky Behavior Detection

To detect risky driving behavior, two GMM-based driver-behavior models were employed to capture patterns of driver behavior from a set of observations belonging to safe driving-behavior and risky driving-behavior groups, i.e., $\Theta_{\text{safe}}$ and $\Theta_{\text{risky}}$, respectively. Again, the observations are obtained from common driving signals such as gas pedal pressure $G$, brake pedal pressure $B$, steering-wheel angle $S$, vehicle velocity $V$, and following distance $F$. Both models were trained using the manually tagged data of the development set. Subsequently, they were used to perform a hypothesis test to determine whether an unseen event with observations $O$ is classified as safe or risky [20] as

$$\text{An event is risky if} \qquad \frac{p(O|\Theta_{\text{risky}})}{p(O|\Theta_{\text{safe}})} \geq \gamma \quad (8)$$

where $\gamma$ is a predefined threshold.

To validate the detection performance of the GMM-based driver-behavior model, a sixfold cross validation was performed to detect hazardous situations of types 8 and 9 (i.e., risky obstacle avoidance and risky driving through an uncontrolled intersection) using observations from 1786 and 833 events, respectively. Fig. 4 shows receiver operating characteristic (ROC) curves of (left plot) risky driving detection performance of the risky obstacle avoidance and (right plot) the risky driving through an uncontrolled intersection, employing different sets of observations (i.e., $O = [B, G, S, V, F]^T$, $O = S$, or $O = B$). As we can see, adding more observed driving signals showed better detection performance.

To further improve the detection performance, an additional feature capturing the residual of pedal prediction could be appended to the observed feature vector. This prediction residual represents the degree of a driver behavior actually observed that deviates from the predicted value of a driver model. To calculate the prediction residual, we first built a global driver-behavior model for gas-pedal prediction, as mentioned in the previous section, using observations from a pool of several drivers. The obtained global driver-behavior model represents average or general driving characteristics commonly shared by all training observations. This global driver model was then used to predict pedal operation $\hat{G}_{t+\tau}$ of a driver. Subsequently, the deviation of the actually observed value from the predicted value (i.e., $G_{t+\tau} - \hat{G}_{t+\tau}$) can be obtained at each time sample of a driving event. Then, we appended this value to a feature vector $O$ (i.e., $[B, G, S, V, F, G - \hat{G}]^T$) to obtain a new feature vector for training $\Theta_{\text{safe}}$ and $\Theta_{\text{risky}}$ and for a hypothesis test in (8). As shown in Fig. 4, adding the prediction residual of pedal signals consistently improved prediction performance. In general, about 70% of risky driver response could be detected

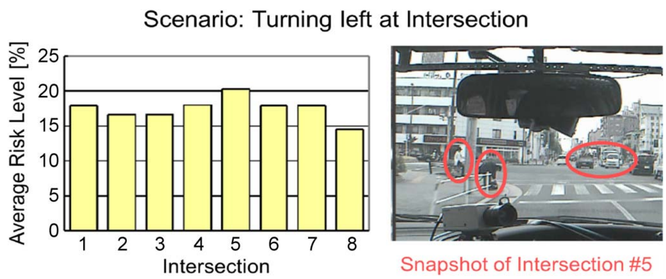



Fig. 5. Comparison of traffic-context risk during left turn at different intersections.

with a 20% false positive rate. We then exploited this new feature for detecting risky driving behavior in our study.

## D. Analysis of Potential Risks

To quantify the hazardous situations previously discussed and analyze the driving data, we define the levels of potential risk of a driver's response to a traffic situation and the risk of the traffic situation itself with the following two parameters:

$$\text{Potential risk of a traffic context } (\alpha) = \frac{Obs}{All} \tag{9}$$

$$\text{Potential risk of a driver } (\beta) = 1 - \frac{Rsp}{Obs} \tag{10}$$

where $Obs$ is the number of observed hazardous situations in a particular traffic context (e.g., turning left at the intersection of A and B streets), $All$ is the number of all possible hazardous situations, and $Rsp$ is the number of appropriate responses made by drivers to the hazardous situations. That is, $\alpha$ represents the risk level of a traffic context, and $\beta$ represents the risk level of a driver's response.

We analyzed the driving data of 86 drivers, including three expert drivers (i.e., driving instructors). All of the drivers drove the instrumented vehicle along the course for the first time with a secondary task (e.g., talking on a hands-free cell phone, performing command input through a speech interface, etc.), but they drove the course the second time without any secondary tasks. Fig. 5 compares the levels of scene danger when turning left at eight different intersections. Among intersections with traffic lights, the level of scene danger at the fifth intersection is the highest due to its high traffic volume and the large number of pedestrians. Similarly, Fig. 6 compares (left) the absence of appropriate driver reaction between nonexpert and expert drivers and (right) the lack of appropriate driver reaction while driving with and without secondary tasks. We can see that non-expert drivers showed higher level of potential risk, compared with expert drivers, and that driving without secondary tasks resulted in a lower level of potential risk than driving with secondary tasks.

# V. Driving Diagnosis and Feedback System

In this section, we describe our proposed system, which allows drivers to review their own driving data as recorded by a CDR, using an automatic method to detect hazardous behavior based on the aforementioned algorithms [4].

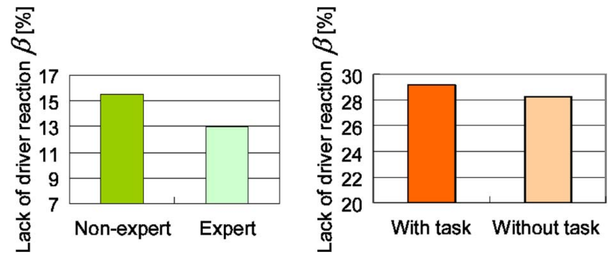



Fig. 6. Comparison of driver risk levels. (Left) Nonexpert versus expert. (Right) With task versus without task.

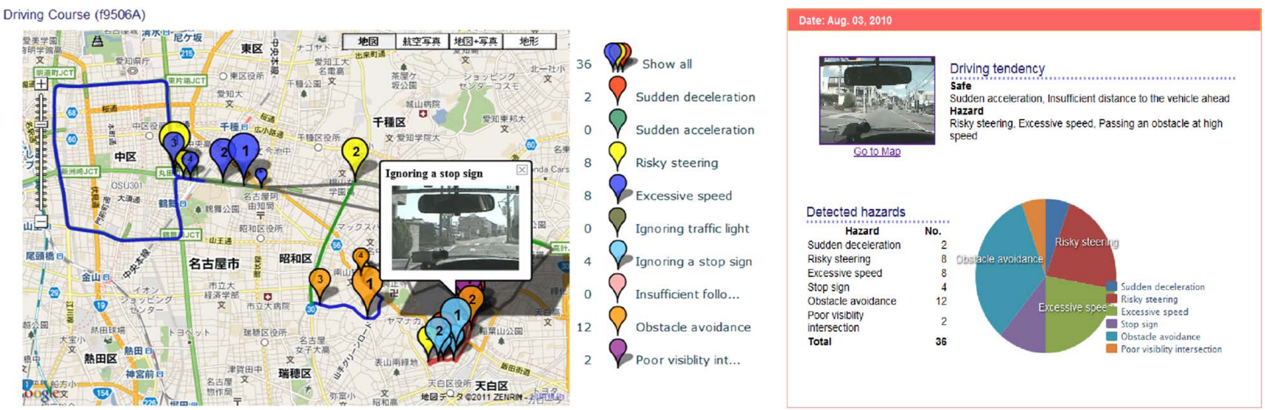
## A. System Description

Our automated diagnosis and self-review system was developed on a server computer as a web application using computer-generated imagery for easy access via networks from personal computers or smartphones. Our system automatically detects nine types of potentially hazardous situations (Table I) from the driver's own recorded driving data. The current version will display up to five of the most hazardous scenes of each hazard type by automatically gauging the hazard level using the magnitude of the difference from the predefined thresholds (for hazard types 1–7) or from the magnitude of the likelihood ratio between the risky and safe driving models (for hazard types 8 and 9). The system allows users to browse through each detected hazardous situation, represented by a balloon icon on an actual driving map (i.e., Google Maps API). Each balloon represents one hazardous situation, with different colors corresponding to different hazard types. The bigger the size of a balloon, the higher the hazard level, as shown in Fig. 7(a). The system also provides statistics on all the hazardous situations the driver was involved with, from all the recorded data, using a pie chart showing the number of occurrences of each type of hazardous behavior. Therefore, the system can identify a tendency toward risky driving behavior or other personality traits possessed by an individual driver, as shown in Fig. 7(b).

After clicking on the balloons on the driving map, the corresponding video clip and driving signals are displayed, along with instructions on how the user can improve their driving behavior. The user can also examine various kinds of driving signals related to that particular driving scene. The safety instructions were prepared in advance for each type of detected hazardous situation, based on the aforementioned manual. Table II shows samples of instructions given in different types of hazardous situations. In general, the system will inform the user of why a particular driving behavior is considered unsafe in that situation and then advise the user on how they can improve their driving behavior. Fig. 8 shows an example of the interface diagnosing a hazardous situation at an intersection. The system notifies the user that the user did not stop at the stop sign and crossed the intersection at a speed of 17 km/h. Then, the system suggests that the driver should completely stop at the stop sign and confirm that it is safe to cross the intersection before proceeding.

## B. Experimental Evaluation

To validate the effectiveness of our developed system in reducing the number of detected hazardous situations, we recruited 33 drivers, including six expert drivers, to participate




(a) (b)

Fig. 7. Interface summarizes hazardous situations on a driving map, along with driving tendencies of user.

TABLE II
SAMPLES OF INSTRUCTIONS GIVEN FOR DIFFERENT TYPES OF HAZARDOUS SITUATIONS

| Types | Sample Instructions |
|---|---|
| 1) | The vehicle lurched due to sudden braking.<br>Please pay attention to the road and try to brake more gradually. |
| 2) | The vehicle accelerated suddenly. Take it easy!<br>Don't be in such a hurry. |
| 3) | Abrupt steering was detected. This is a leading cause of lateral collisions.<br>Please slow down, so you can stay in your own lane when turning. |
| 4) | When you entered the curve, your speed was too high.<br>Please decelerate before entering a curve. |
| 5) | You may have driven at an unsafe speed. Haste and impatience may<br>lead to an accident. Please allow sufficient travel time and travel at<br>a similar speed to the other vehicles. |
| 6) | This is an intersection with a stop sign or with poor visibility.<br>There is possibility of a sudden collision. Please stop completely at the<br>stop line and confirm that it's safe before entering the intersection. |
| 7) | You may have gone through an intersection at the last moment,<br>after the light turned yellow. A yellow light also means "stop".<br>Please try to predict when the light will change.<br>If there are pedestrian signals, it may be easier to predict signal changes. |
| 8) | There may have been an obstacle on the side of the road.<br>Try to avoid obstacles safely by keeping a safe distance to your left. |
| 9) | There may be hidden pedestrians and vehicles at the intersection.<br>Please keep sufficient distance or slow down. |

in our experiment. The subjects were asked to drive the instrumented vehicle three times on three different days, following the same route, which takes approximately 1.5 h to complete. We used data from the second and third sessions for our analysis, as we allowed the subjects to get familiar with the instrumented vehicle during the first session. The subjects were scheduled to have their second session a few months after their first session. A few weeks after participating in the second session, some of the subjects used the driving coaching system and received safety feedback for 10 min before taking part in the third session. The subjects only received a brief tutorial on how to use the system and then browsed their own data after being instructed to review all of the detected hazardous driving situations in any order. They were told that, if time remained, they could also view their normal driving data or any other information. The system recorded logs of their browsing behavior using software to capture screen images.

We compared the number of detected hazardous situations from the second and third sessions. Fig. 9 compares (top) the number of detected hazardous scenes for drivers who received coaching using our system and those who did not and (bottom) the number of hazardous scenes detected for normal and professional drivers. The top of the figure shows the number of hazardous situations detected for six drivers who did not use the coaching system. (These data were collected from another six drivers, in addition to those among the 33 drivers who did use the coaching system.) The bottom of the figure compares the number of detected hazardous incidents among the 27 nonexpert drivers and the six expert drivers, all of whom used the system, both before and after coaching. We observed

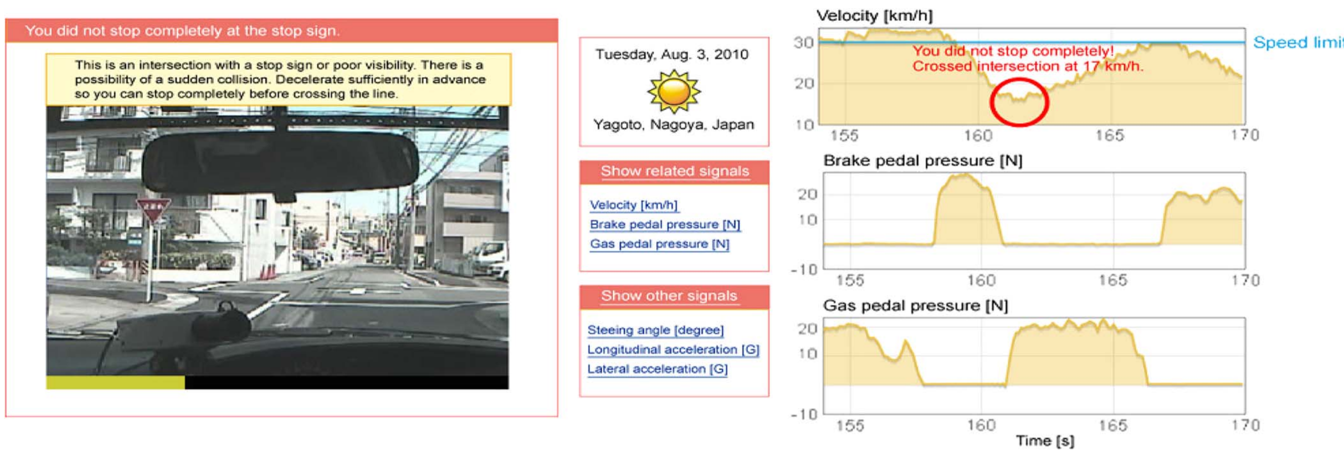



Fig. 8. Example of interface diagnosing hazardous situation at an intersection.

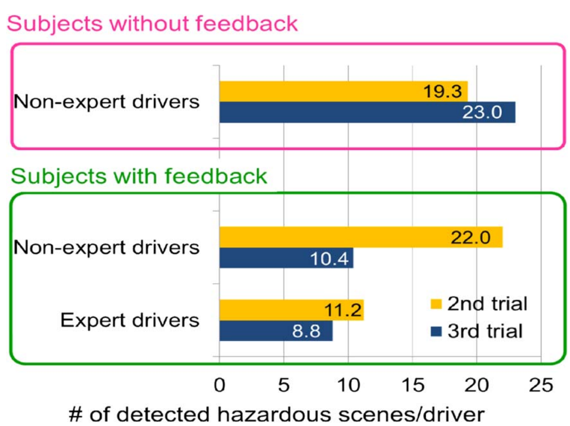



Fig. 9. Number of detected hazardous scenes for subjects who did not receive feedback and nonexpert/expert drivers before and after receiving feedback.

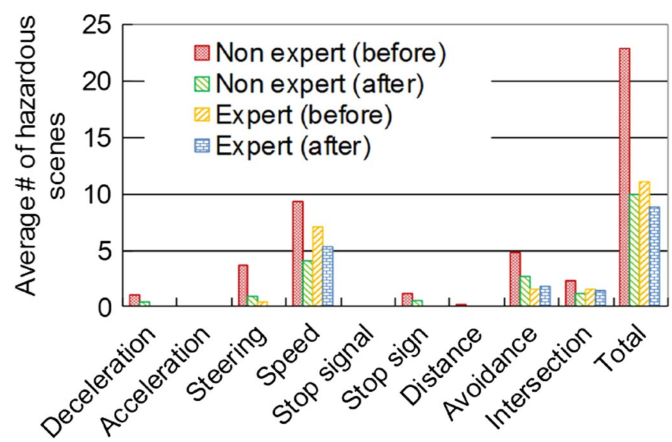



Fig. 10. Comparison of the average number of hazardous situations for all drivers before and after using the system under different types of hazardous situations.

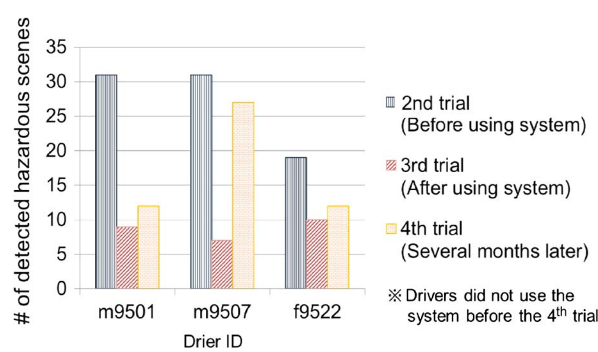



Fig. 11. Comparison of the number of detected hazardous situations during the second, third, and fourth sessions for three drivers.

no improvement among the drivers who did not use the system. On the other hand, the number of detected hazardous scenes decreased by approximately 50% for the nonexpert drivers who reviewed their risky driving behavior before participating in the third session. Among the 33 drivers who used the system, the number of detected hazardous situations decreased for 27 drivers. We also observe that the number of detected hazardous scenes of expert drivers was much smaller than that of nonexpert drivers for the second drive; however, there was no significant improvement on the third drive for the expert drivers.

Fig. 10 compares the average number of detected hazardous situations before and after using the system for all drivers, categorized into different types of hazardous situations. The number of detected hazardous scenes for expert drivers was about half the number detected for nonexpert drivers. In addition, the number of detected hazardous scenes for most of the nonexpert drivers decreased by approximately 50% for all types of hazardous situations after using the system, whereas less impact was observed with the expert drivers.

A preliminary study was performed to further examine the impact of the system on long-term driving behavior, and three drivers were asked to participate in the experiment a fourth time, several months after participating in the third session. For the fourth session, the drivers were not allowed to use the coaching system before driving. Fig. 11 compares the number of detected hazardous situations for the second, third, and fourth sessions of these three drivers. We can see the number of detected hazardous scenes during the fourth session was higher than that during the third session but still lower than the number detected during the second session. This showed that drivers had forgotten some of what they had learned by the time of the fourth session but that their driving behavior was still better than before using the coaching system. This suggests that repetitive training is necessary to maintain long-term driver safety awareness.

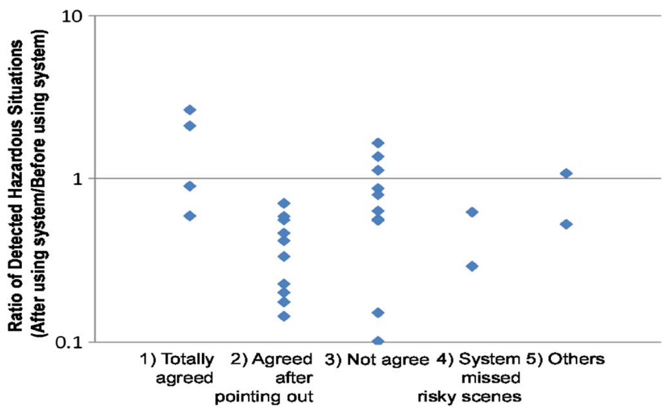



Fig. 12. Drivers' subjective agreement on detected hazardous situations versus driving performance after/before using system (one marker/driver).

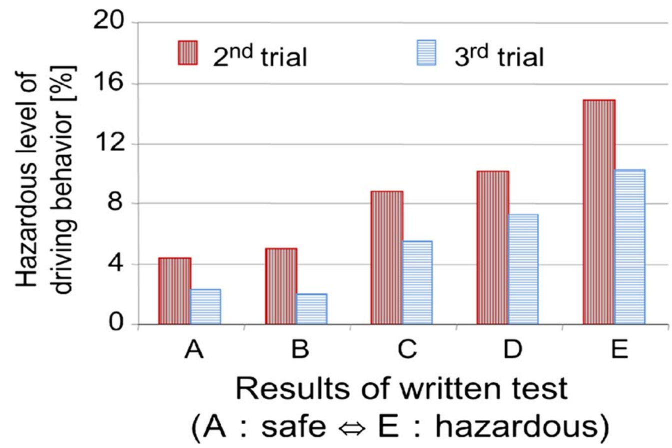



Fig. 13. Relationship between the results of a written driving test and actual driver behavior.

In addition, we surveyed the drivers to discover their subjective opinion of the hazardous situations detected by the system using a questionnaire. The drivers' opinion can be categorized into the following groups:

1) drivers who realized that the situations were risky themselves during driving, and who agreed with the system after watching the scenes;
2) drivers who did not realize that the situations were risky but who agreed with the system after watching the scenes;
3) drivers who did not agree that the situations were risky;
4) drivers who realized that the situations were risky but who felt the system failed to detect other hazardous behavior;
5) others.

Fig. 12 plots drivers' opinions (groups 1–5) and their driving performance in terms of the ratio of the number of detected hazardous situations after and before using the system. (A ratio value of less than 1.0 represents a decrease in the number of detected hazardous situations after using the system.) We can see that about 50% of drivers agreed that the hazardous situations detected by the system seemed to be hazardous to them. Subsequently, the majority of drivers who improved were those who adopted the senses of hazardous situations.

Finally, to analyze possible correlations between individual driver characteristics which can be measured with a written test, and the actual driver behavior, we asked the subjects to complete several questionnaires before and after participating in the experiment. We used questionnaires, which we created for this experiment, as well as standard tests used to measure driver safety aptitude [21] and driver safety awareness [22] and two checklists used to predict driving style and sensitivity to stress while driving [23]. Fig. 13 shows the relationship between the results of a written driver test and the actual driving behavior. We can see a correlation between driver risk levels as predicted using a written questionnaire designed by traffic psychologists and the actual driving behavior. The figure shows that drivers who were judged to be more dangerous by results of a written test actually showed more dangerous behavior during the study. We also observed that the safer drivers exhibited more improvement in their driving behavior after using the system than drivers with riskier driving behavior.

## VI. Conclusion and Future Work

We have developed an algorithm for the automatic detection of potentially hazardous driving situations, including latent hazardous situations, which conventional EDRs cannot capture. The algorithm employed GMM-based driver-behavior modeling to identify whether a situation is considered safe or risky. As a result, we were able to detect various kinds of risky driving behavior. We then developed a web-based driver coaching system that allows users to review their own recorded driving scenes, as well as corresponding driving signals such as speed, brake, and gas pedal pressures. The proposed system is capable of automatically detecting hazardous situations and instructing users how to appropriately respond to such situations in a safe manner. The experimental results have shown that the amount of risky driving behavior detected was reduced by half after drivers used our proposed system. In future work, we aim to analyze a greater number of drivers on repetitive training using our system and its impact on their long-term driving behavior, as well as to quantify the advantage of having drivers review their own and other drivers' driving scenes. Furthermore, we hope to detect more types of unsafe driving behavior by monitoring the driver's gaze and foot position in relation to pedal operation. We are also developing a smaller EDR, which can be installed in a wide variety of vehicles. This data recorder will also allow communications between controller-area-network bus information and smartphones.

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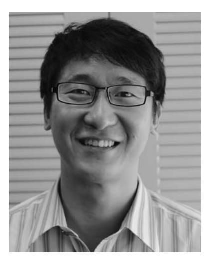

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