INTEGRATED MEASURES FOR AGGRESSIVENESS AND SIMILARITY OF DRIVING BEHAVIOR USING MULTIPLE SENSOR SIGNALS

LI Yiyang

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複数センサ信号を用いた運転行動の荒さ及び類似度の統合的尺度

Department of Media Science
Graduate School of Information Science
Nagoya University
Nagoya, Japan

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Abstract

Due to the development of multiple automotive sensors, such as drive recorders, cameras, LASER scanners and even in-vehicle networks, large volumes of various real-world driving data can now be accurately recorded. These raw driving data contain valuable information about driver's behavior and situations, and by analyzing and understanding them, we can help make driving safer and more comfortable. However, these raw driving data cannot be easily interpreted directly. One of the key steps to utilizing them effectively is data abstraction. Data abstraction can be defined as the process of extracting useful features and then integrating these features to interpret a certain driving behavior or situation, such as an evaluation of driver's behavior, or recognition of a driving event. The volume of various driving data recorded by multiple sensors can be quite large, and in order to empirically select meaningful segments for further analysis, they have to be manually reviewed, which can be an unintentionally subjective process. Manual selection of data segments is very time consuming and may lead to biased research results, therefore the development of an automated data selection and abstraction process would be desirable. In this dissertation, we present two studies focusing on the following two abstraction processes:

I. Extraction of useful features from various types of driving signals recorded

by multiple sensors.

Ⅱ. Integration of these features in order to interpret driving behavior.

In the first study, the aggressiveness of driving behavior is evaluated using three kinds of driving data recorded by drive recorders. In order to score driver aggressiveness, seven different feature variables are extracted and then integrated. The assumption here is that vehicle motion is mainly controlled by the driver's operation of the steering wheel and the gas and brake pedals, and the aggressiveness of driving behavior is evaluated by focusing on four operational sub-behaviors; steering behavior, acceleration behavior, deceleration behavior, and alternation between acceleration and deceleration behaviors. After assigning aggressiveness scores to each of these sub-behaviors, the overall aggressiveness of a driver's behavior is estimated by integrating the aggressiveness scores of the sub-behaviors, using multiple regression.

In the second study, six types of driving data are used to measure the similarity of driving behaviors and to retrieve driving data for similar types of behaviors. Three features are extracted and integrated to measure the similarity of driving behavior. Driving is a complex decision-making process due to the dynamic relationships between the three major entities involved, which are the driver, the driver's vehicle, and the environment. Information about driving behavior can be obtained from intra-vehicle driving data, as well as from the positions and motion of surrounding vehicles and from road information. Dynamic features of these three entities are used to extract data representing similar driving behaviors.

The performance of the proposed methods is integrated in both studies with evaluation experiments, using various combinations of feature variables, and then the results are compared with the ground truth and with conventional data analysis methods. According to the evaluation experiment in the first study, the proposed multiple linear regression model achieved a correlation coefficient of 0.64 in relation to the empirical evaluations of the risk consulting experts. By applying principal component analysis to the feature sets, prediction performance was improved and a correlation coefficient of 0.74 was obtained. Experimental results in the second study showed that the additional use of environmental information significantly improved the precision of retrieval of similar driving scenes compared with a conventional method. According to the results, different people were found to focus on different elements when comparing driving scenes, which may indicate that different drivers focus on different phenomena while driving.

Thus, the effectiveness of the proposed driving data abstraction methods were confirmed through the two studies.

Chapter 1

Introduction

Ever since the first automobile accident in 1771, and the first recorded automobile fatality, in 1869, human error has been cited as the primary cause of automobile accidents [1]. Indeed, human error has even been cited as the cause of one of the first railway fatalities in 1831 [2]. Two centuries later, human error is still responsible for many accidents, in various modes of transportation such as motor vehicles, trains, and airplanes. But as technology has evolved, safety systems have been developed to help mitigate these errors and help operators avoid dangerous situations. In the case of automobiles, safety was improved simply by requiring brakes to be installed on automobiles, and these improvements have evolved into the much more advanced technologies used in modern driver assistance systems. Despite these safety measures, there are still a huge number of deaths and injuries every year on roadways around the world, and studies have shown that driver error is still the major cause, cited in more than 93% of traffic accidents [3]. Thus it is clear that drivers, as well as their driving behavior, should be carefully studied as important factors contributing to traffic accidents. However, prior to the development of modern information technology, it was difficult for researchers to collect data on real-world driving behavior.

Many types of sensors have now been developed, which make it increasingly easy for researchers to collect large volumes of a wide variety of real-world driving data [4–8]. Older sensors, such as speedometer sensors, calculate vehicle velocity using tire rotation, while others can be mounted inside or outside of vehicles, such as omni-directional cameras [9, 10] and LASER-scanners [11, 12]. Data can also be obtained directly from a vehicle's onboard computer system. The use of multiple sensors allows us to collect not only intra-vehicle driving data, such as velocity, acceleration, and steering angle, but also information about the surrounding environment, e.g., the type of road the driver is traveling on and the locations of surrounding vehicles. There are currently hundreds of instrument-equipped vehicles in operation around the world collecting real-world driving data [13, 15, 54]. Vehicle sensor suites include video cameras, controller area networks (CAN), GPS and laser scanners, which allow us to monitor almost all of the driving process. In the future, it will be possible to connect vehicles to Internet data collection centers, allowing a wider range of driving data to be easily acquired.

Some researchers from Japan, Europe, and the USA are working together to collect these data and are building a large, international driving data corpora for research on driver behavior [16]. A project, called European Field Operational Test (euroFOT), was lead by Ford with 28 partners, including most European vehicle manufacturers [17]. This project involves test on 1,000 vehicles during a one-year period and 30 TB of data that are gathered for future analysis and research. In order to make the driving safer, the United States Congress created

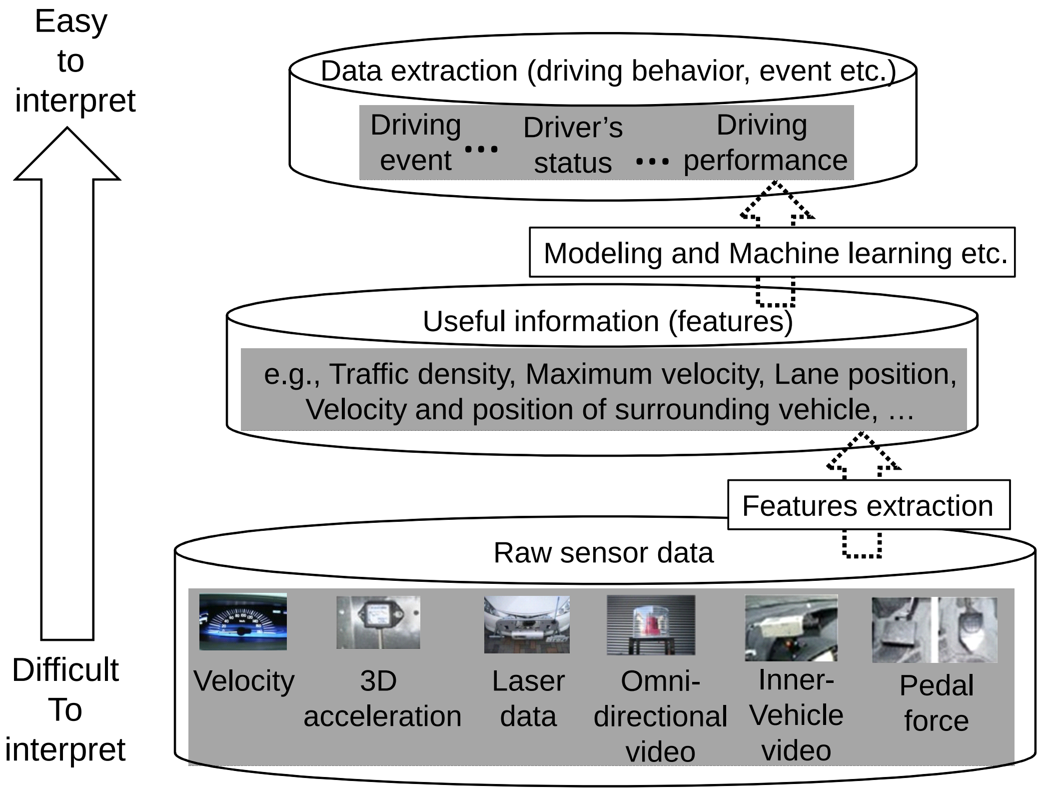

Figure 1.1: Three levels of data abstraction.

the second Strategic Highway Research Program (SHRP 2) [18]. It is a naturalistic driving study that investigates ordinary driving under real-world conditions. In the SHRP 2 study, about 3,000 volunteer drivers agreed to have their cars equipped with cameras, RADAR, and other sensors to capture data as they go about their usual driving tasks.

Analysis of these data will not only help researchers understand the causes of traffic accidents, but may also aid in the development of new driver assistance systems, which will make driving safer and more comfortable [19, 20]. The various sensors of instrumented vehicles collect raw, unprocessed data which is not immediately useful or understandable without data analysis. So, in order to utilize these data, data abstraction is necessary. As shown in Fig. 1.1, data abstraction in this context is the process of extracting features which provide information regarding a certain driving behavior or event, and then combining the extracted features for the purpose of representing driving behavior. This data abstraction process consists of three levels. The bottom level is the sensor level, which represents the raw sensor data that is collected from various sensors mounted on the vehicle. The median level is the feature level, which consists of various features extracted from raw sensor data, such as traffic density, maximum velocity, lane position, velocity and position of surrounding vehicle, distribution of surrounding vehicles, average velocity, etc. The uppermost level is the driving behavior or event level, at which feature level data is combined to detect driving events, to evaluate driving behavior, and to infer a driver's awareness status, etc. The data abstraction process is necessary in order to better understand the collected data. Generally, researchers have to manually review all of the data that has been collected and then select meaningful segments out for further analysis, which is a time-consuming task that can be quite subjective.

In this dissertation, I will discuss data abstraction techniques, explain how useful features can be extracted from raw sensor data, and describe how these features can be combined to measure and evaluate driving behavior. In the first study, the aggressiveness of driver behavior is evaluated using three kinds of driving data recorded by a drive recorder. Seven features from the raw sensor data are extracted and integrated to find suitable representations of driver aggressiveness. In the second study, six kinds of driving data are recorded by laser-scanner and several intra-vehicle sensors. Three features are extracted to represent intra-vehicle information, road information, and surrounding vehicles information. They are used as an integration to retrieve similar driving scenes.

This dissertation is structured as follows. In Chapter 2, related research and general background information regarding data abstraction is discussed. The driving aggressiveness evaluation study is described in Chapter 3, followed by a description of measure for similarity of driving behavior study in Chapter 4. In Chapter 5, I discuss the conclusions of this dissertation and future directions for related research.

Chapter 2

Related Studies

In this chapter, we survey recent driving data abstraction techniques employed by other researchers. Since these techniques form the basis of driving behavior analysis, many articles have been written on this topic [21–23]. Eye movement data has been used to evaluate driver distraction [24–27]. Lane change events have been used to estimate driving behavior characteristics which may lead to accidents [28–30]. McLaughlin et al. [31] and Lemelson and Pedersen [32] studied vehicle location within driving lanes was studied to investigate its relationship to collision avoidance. Variability in lane position has been used to identify levels of driver fatigue and drowsiness [33–35]. Information on traffic conditions, e.g. traffic density, has been used to evaluate cognitive capability and attentiveness of drivers [36–38]. In all of these studies, raw recorded data were converted into meaningful feature variables, and the extracted feature variables were then used to represent driving behavior and to indicate behavioral patterns. Some of these studies are closely related to the work presented in this dissertation, and will be discussed further in the following two sections.

2.1 An overview of driving behavior evaluation

Because drivers drive more safely when being monitored, auto insurance companies have begun placing sensors such as drive recorders in commercial vehicles to monitor driver behavior. The data is then manually interpreted by experts [39, 40]. However, this approach is very costly and time-consuming [41]. As a result, some automated techniques have been developed to evaluate driving behavior, but most studies focus on some special driving operations, such as brake pedal operation, or the driving behaviors involved in some special driving events, such as turning and lane change. Thus, a comprehensive, automated driver evaluation system which can produce an overall evaluation of driver behavior has not been discussed yet.

2.1.1 Classification of rapid deceleration patterns

Naito et al. used a clustering method to identify the characteristics of driver's braking behavior [42]. Their proposed method tracks how drivers depress and release the brake pedal while driving and then evaluates the danger of each braking operation. All of the braking behavior evaluated in their study was considered risky, i.e., causing rapid longitudinal deceleration of more than 0.3 G. Each braking operation was recorded by a drive recorder as an event of one minute in length at first. They then extracted 6.4 second segments of acceleration signals matching the intervals of depressing and releasing the brake pedal, as shown in Fig. 2.1. By examining how drivers adjusted their braking behavior to various traffic situations, these segments were classified into one of four typical braking patterns using the Linde-Buzo-Gray (LBG) algorithm [43]. The four typical braking pat-

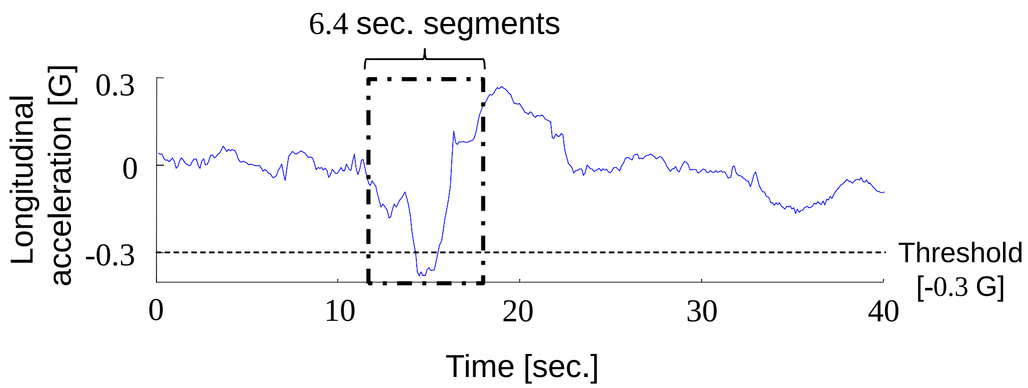

Figure 2.1: Example of a 6.4 sec. acceleration signal segment recorded by a drive recorder, which is extracted from a one-minute piece of data recorded when a strong (above 0.3 G) acceleration or deceleration is detected. The length of a segment was designed to match the approximate interval required for a driver to depress and release the brake pedal.

terns included emergent braking, intensive and long braking, situationally-aware braking, and moderate braking. Utilizing these braking patterns as feature variables, the risk level of a driver's braking behavior was scored on a scale from one to five, based on three proposed criterion; danger, uniqueness, and unsteadiness. However, only driver's brake pedal operation was discussed in their research. In the following Chapter 3, we will discuss about integrating more driving operations, such as steering and gas pedal operations, to achieve an overall evaluation of driving behavior.

Data segments

In their research, a "segment" is a 6.4 sec acceleration signal extracted from an event, as shown in Fig. 2.1. It is extracted from a one-minute piece of data recorded when a strong (above 0.3 G) acceleration or deceleration is detected. The length of a segment was designed to match the approximate interval required for a driver to depress and release the brake pedal.

2.1.2 Driving style recognition

Johnson et al. [44] proposed a novel system that uses a dynamic time warping (DTW) algorithm [45] and smartphone-based sensor-fusion (accelerometer, gyroscope, magnetometer, GPS, and video) to detect, recognize and record aggressive driving behavior. Nearly all (97%) of aggressive driving events were reportedly correctly identified using the proposed method. Their study divided each driver's driving style into one of two categories; non-aggressive and aggressive. The following driving events were examined to evaluate the drivers:

- Right turn (90°)
- Left turn (90°)
- U-turn (180°)
- Acceleration
- Braking
- Lane change

To detect these driving events, driving data were recorded using an smart phone containing accelerometer and gyroscope sensors. The proposed detection and recognition system continuously collects motion data from the accelerometer and gyroscope in order to detect specific maneuvers. The timing of the start or the end of a maneuver is determined by using endpoint detection, and then calculated by a simple moving average. The length of an event is set to be less than 15 seconds. Once a signal representing a maneuver is detected, it is compared to stored maneuvers (templates) to determine whether or not it matches an aggressive event, using a dynamic time warping (DTW) algorithm. The template with the lowest warping path cost is considered to be the closest match. Their proposed method for driving behavior evaluation is based on individual different driving events. In each driving event, driving style is divided into non-aggressive or aggressive. In Chapter 3 of this dissertation, we will discuss how to evaluate driving behavior in normal driving.

2.2 An overview of driving behavior recognition and retrieval

For some applications, it would be very helpful if similar driving behavior patterns or driving events could be automatically retrieved from a database.

2.2.1 Driving event recognition

In order to achieve driving event recognition, Mitrovic trained a discrete hidden Markov model (HMM) using data collected with an acceleration sensor [46]. He confirmed with an experiment that a recognition accuracy of almost 100% can be achieved for some simple driving events. However, this method requires manual annotation hundreds of events in order to train the discrete HMM, which is very time-consuming. In the following Chapter 4, we will propose a method to retrieve the same type of driving events automatically.

2.2.2 Driving behavior retrieval

An automated driving behavior retrieval technique was also proposed by Naito et al. [47]. Using the technique proposed in their study, they achieved a retrieval

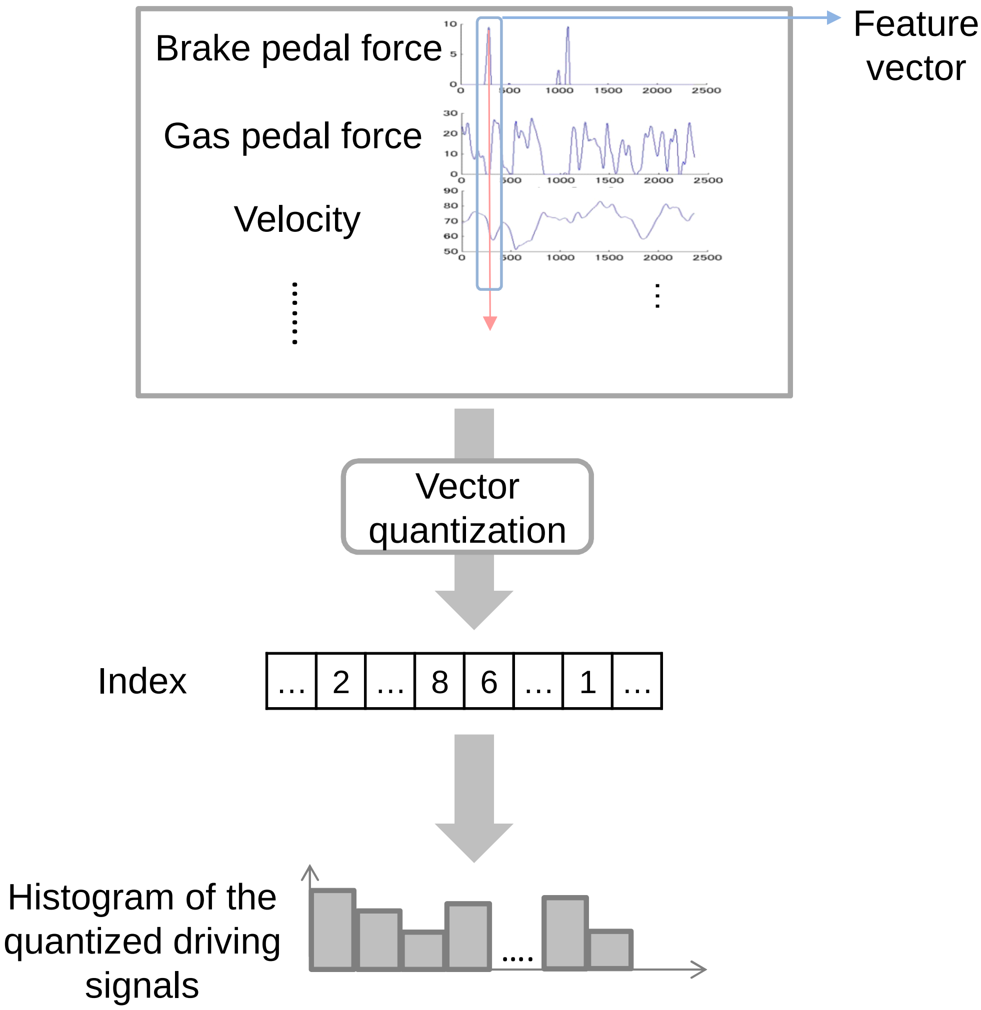

Figure 2.2: Process of driving scene retrieval by Naito et al. [47].

performance of more than 97% for scenes of left or right turns, and for scenes of driving on curves, using a combination of steering angle and lateral acceleration data. Their system calculated the similarity between an input scene and scenes stored in the database by shifting the stored scenes forward in time. A time-series active search algorithm was then used to detect scenes whose similarity exceeded a threshold value [48]. To calculate the similarity between scenes, they employed driving data from the NUDrive Project [49], which included vehicle velocity, following distance, steering angle, pedal pressures, and lateral and longitudinal acceleration of the vehicle. As shown in Fig. 2.2, driving data was concatenated at each sample point into a vector using an LBG algorithm, and then quantized as index sequences. The distance between histograms was then used as a representation of the distance between two scenes. The authors suggested that retrieval performance could be further improved using feature extraction methods as well as a wider variety of driving data. Their findings were the primary motivation for the research described in Chapter 4. Since only intra-vehicle driving data was employed in their study, some situations such as lane change and driving on curve might be hard to be differentiated. In Chapter 4 of this dissertation, internal and surrounding driving data will be employed as an integration for similar driving behavior retrieval.

Chapter 3

Integrated Measure for Aggressiveness of Driving Behavior

Keywords in this chapter:

- Driving behavior evaluation
- Drive recorders
- Aggressive driving
- Multiple linear regression
- Principal component analysis

3.1 Summary of the chapter

In this chapter, 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 aggressiveness of 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 behavior between acceleration and deceleration. In the proposed method, an aggressiveness scores is assigned to each of these behaviors, and a driver's overall aggressiveness score is then estimated by integrating these behaviors using multiple linear regression. The aggressiveness of 78 drivers were assessed by the proposed method, and compared with the aggressiveness scores given 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.

3.2 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 [50], and similar findings have also been reported in publications of the U.S. National Highway Traffic Safety Administration (NHTSA) [51]. According to a report released by the Japanese Ministry of Land, Infrastructure, Transport and Tourism in 2012, 31.7% of serious traffic accidents involving taxies, trucks, and buses were caused by improper vehicle operation [52], 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 [53]. 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 [40]. It has also been reported that the number of traffic accidents could be reduced by 30 to 80% using this method. 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 [42]. Miyajima et al. identified risky driving behavior by independently evaluating steering behavior, acceleration behavior, and deceleration behavior [54]. 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 [44]. In contrast to previous methods of driving behavior evaluation, I propose a quantitative method of evaluating the overall aggressiveness of driving behavior in this chapter.

Although researchers have defined aggressive driving behavior in various ways

[55–57], here we assume that by observing a driver's operation of the steering wheel, gas pedal, and brake pedal, driving behavior can be evaluated. Four vehicle operation behaviors, namely, steering behavior, acceleration behavior, deceleration behavior, and alternation behavior between acceleration and deceleration, are used 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, the aggressiveness scores of the four vehicle operation behaviors mentioned above are used. The aggressiveness of steering behavior is measured using vehicle speed and the minimum radius of road curvature as specified by a road construction ordinance [58]. In order to measure the aggressiveness of acceleration behavior, a two-dimensional plane is used to compare the maximum longitudinal vehicle acceleration and vehicle velocity when the maximum acceleration is observed. The aggressiveness of deceleration behavior is measured by observing the frequency of rapid braking. To measure alternation behavior between acceleration and deceleration, vehicle velocity, longitudinal acceleration, and jerk are used. 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 corporate vehicles, the proposed method is then evaluated experimentally by comparing the results obtained by the proposed method to those by risk consulting experts, who empirically evaluated the aggressiveness of the same drivers using the same recorded data.

In the following section, the proposed method to measure aggressiveness of driving is introduced. An experiment of driving behavior aggressiveness prediction is presented in Section 3.4. Conclusions and suggestions for future work are presented in Section 3.5.

3.3 Evaluation of driving behavior

To evaluate the aggressiveness of a driver's behavior, three kinds of driving signals, i.e., vehicle velocity, longitudinal acceleration, and lateral acceleration, are used. The assumption here is that these signals can then be used to represent four vehicle operation behaviors; steering behavior, acceleration behavior, deceleration behavior, and alternation behavior 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. Then, the aggressiveness scores of these behaviors are integrated to estimate a driver's overall driving aggressiveness score. The method of obtaining an aggressiveness score for each operation behavior is discussed in Sections 3.3.1 through 3.3.4. 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 each other. Alternation behavior 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 [59]. In addition, feature correlation may reduce the prediction performance of the regression model. Therefore, principal component regression (PCR) [60],

Table 3.1: Features of driving behaviors used to measure aggressiveness.

Sub-behavior	Symbol	Feature
Steering behavior	f_{s}	Proportion of abrupt steering operations
Acceleration behavior	f_{a}	Acceleration from stop
	f_{v}	Driver's preferred speed
Deceleration behavior	f_{b}	Frequency of rapid braking operations
Alternation behavior	$f_{\mathsf{c_v}}$	Standard deviation of velocity
	$f_{\mathsf{c_a}}$	Standard deviation of acceleration
	$f_{\mathsf{c_j}}$	Standard deviation of jerk

which applies principal component analysis (PCA) to the features of each driving behavior is applied prior to linear regression. A driving aggressiveness score (S) is assumed that it can be represented as a regression model, which is defined as:

$$S = \alpha_0 + \alpha_1 p_1 + \alpha_2 p_2 + ... + \alpha_n p_n, \tag{3.1}$$

where α_i is the regression coefficient, and p_i is the explanatory variable of the i-th feature or principal component. The driving behavior features listed in Table 3.1 are used to measure aggressiveness in this study.

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

3.3.1 Steering behavior

A steering behavior is assumed to be 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 [58]. Exact values for maximum

Table 3.2: Relationship between road design speed and minimum radius of curvature as defined in Japanese road construction ordinance No. 15.

Speed limit corresponding to the minimum radius of road curvature [km/h]	Minimum radius of road curvature [m]
20	15
30	30
40	60
50	100
60	150
80	280
100	460
120	710

safe speeds at different radii of curvature are shown in Table 3.2. 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, vehicle motion while steering is approximated as a circular motion, and the radius of the curvature of vehicle trajectory (R) is estimated based on the following circular motion equation:

$$R = \frac{v^2}{a}, \tag{3.2}$$

where a is the 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 3.1 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 the solid lines indicate abrupt steering, whereas the 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.

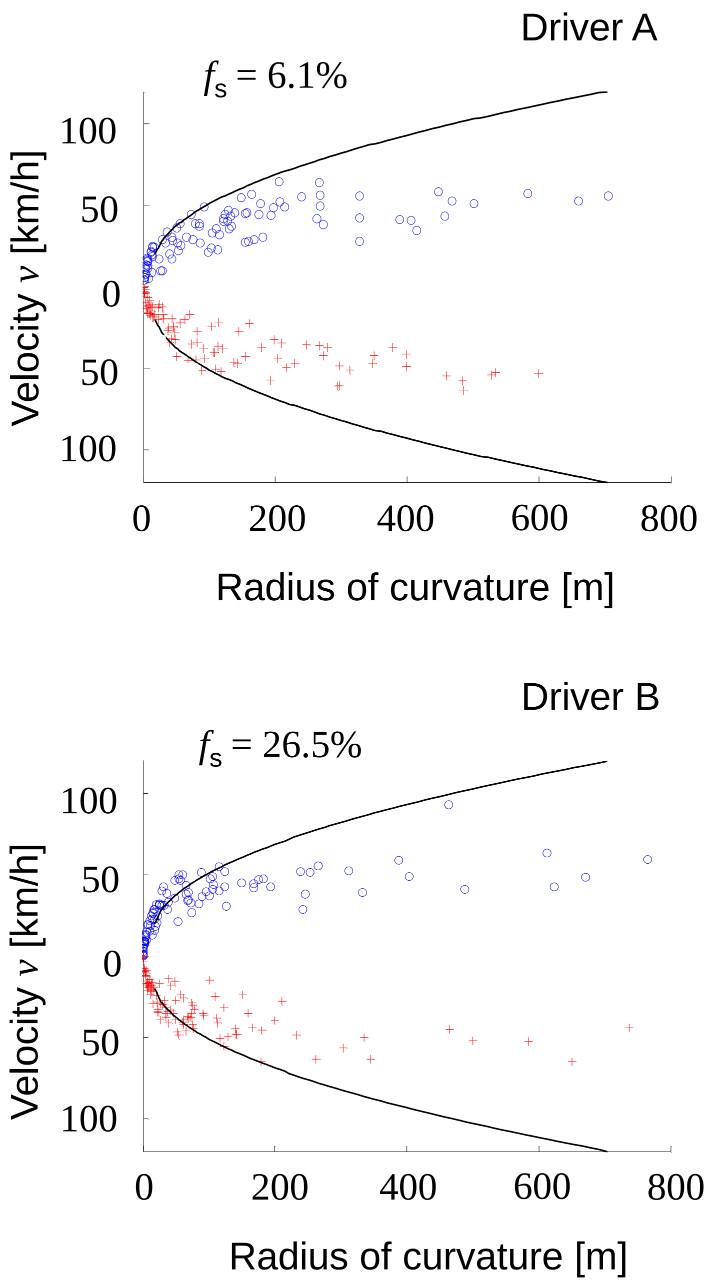

Figure 3.1: Examples of vehicle velocity (v) and estimated radius of curvature (R) for two different drivers ($T = 45$). Upper and lower halves of each graph represent radii of curvature to the right and left, respectively.

3.3.2 Acceleration behavior

Both rapid acceleration and excessive speed are assumed to be indicators of aggressive acceleration behavior. The feature used to measure rapid acceleration, f_{a}, is defined as the 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, a two-dimensional plane is used, whose axes represent the maximum longitudinal vehicle acceleration and vehicle velocity when the maximum acceleration was observed. The maximum longitudinal vehicle acceleration is selected at time interval T, which is determined by a preliminary experiment. Here, the assumption is that each driver has preferred cruising speeds and that the maximum acceleration is almost inversely proportional to velocity; as velocity increases, acceleration decreases. The distribution of driving data in the two-dimensional plane is approximated with a line, and orthogonal linear regression [61] is used to obtain two intercepts, one for each axis. As shown in Fig. 3.2, 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 3.2 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.

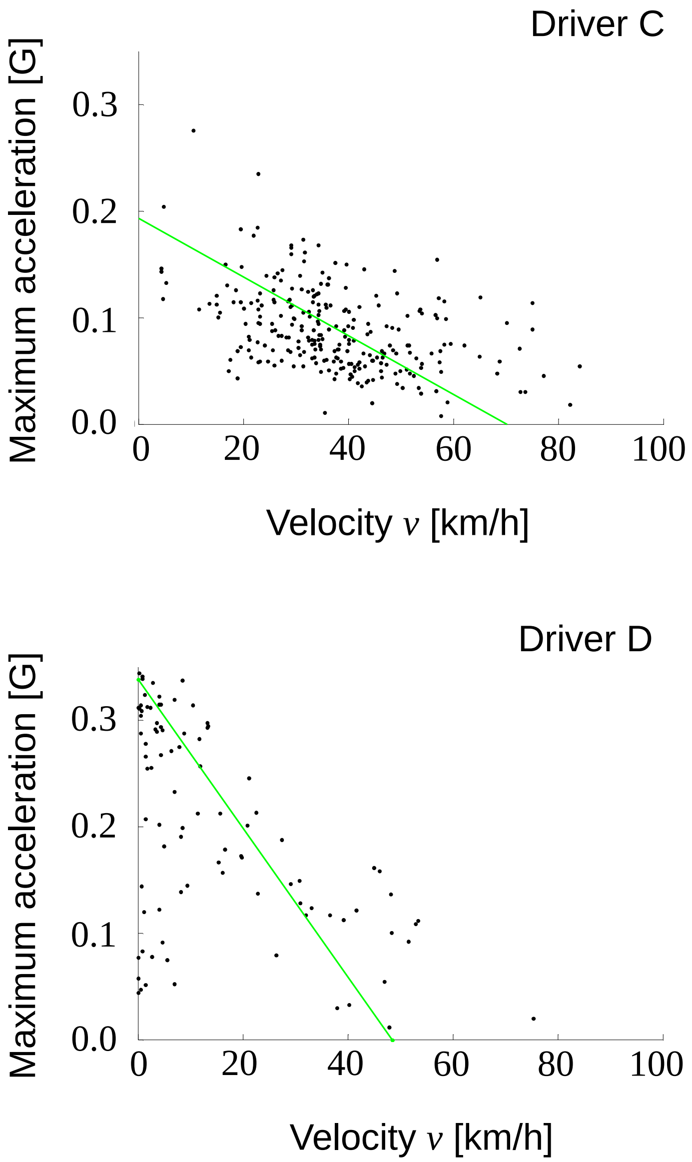

Figure 3.2: Examples of two-dimensional planes for different drivers, showing the maximum longitudinal vehicle acceleration and vehicle velocity when the maximum acceleration was observed ($T = 50$).

3.3.3 Deceleration behavior

Deceleration behavior is assumed to be 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 $\mathrm{m/s^2}$ (0.26 G) [62]. Here, 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_{b}).

3.3.4 Alternation behavior between acceleration and deceleration

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

$$\dot{a}(t) = \frac{\sum_{k=1}^{K} k\left\{a(t+k) - a(t-k)\right\}}{2\sum_{k=1}^{K} k^2}, \tag{3.3}$$

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 ($f_{\mathrm{c_v}}$), acceleration ($f_{\mathrm{c_a}}$), and jerk ($f_{\mathrm{c_j}}$), are used as features to indicate alternation behavior between acceleration and deceleration.

3.4 Experiment

An experiment was conducted to evaluate the effectiveness of the proposed method at predicting aggressive driving behavior. The experiment consists of two parts: 1. Evaluation of the extracted features representing aggressiveness for the four sub-behaviors; 2. Evaluation of the prediction of the overall aggressiveness of a driver's behavior using Eq. (1), by multiple linear regression (MLR) or principal component regression (PCR).

3.4.1 Driving data used for evaluation

The driving behavior signals used for the evaluation were provided by a risk consulting company, and were collected using drive recorders mounted on corporate vehicles, with a sampling rate of 10 Hz. All of the vehicles used for data collection were equipped with the same type of drive recorder, which 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. The driving data were collected from 78 drivers as they drove on city streets and highways from 2005 to 2006, for an average duration of approximately 105 minutes per driver. However, these data are not continuous. They are segment data lasting 10 to 30 seconds in average, and recorded by drive recorder only if some special driving event occurred. Therefore, the actual time for data recording could be much longer than 105 minutes for each driver. The driving behavior of each of the same 78 drivers was

Table 3.3: Distribution of empirical scores given by risk consulting experts, from 1 (least aggressive) to 5 (most aggressive).

Empirical score	1	2	3	4	5
Frequency (# of drivers)	5	10	23	20	20
Total (# of drivers)	78				

also evaluated by the risk consultants based on empirical criteria formulated by an expert who had been working for a risk consulting company for more than ten years. Although details of the consultant's evaluation criteria are not available to the public, aggressiveness scores based on empirical criteria have some correlation to the actual number of traffic accidents, according to the records of the risk consulting company. 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 3.3. Drivers were evaluated once by one expert. The proposed method was evaluated by comparing the aggressiveness score for each driver obtained by the proposed method, with the empirical aggressiveness score given to that driver by the risk consultant.

3.4.2 Evaluation of features used to measure aggressiveness

Spearman's rank correlation coefficients [63] was calculated 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

Table 3.4: Correlation coefficients between aggressiveness features f_s, f_a, f_v, and empirical scores given by risk consulting experts at various time intervals.

T [sec.]	f_s	f_a	f_v
5	0.18	0.34	0.27
10	0.18	0.30	0.29
15	0.18	0.28	0.34
20	0.19	0.28	0.34
25	0.20	0.35	0.32
30	0.16	0.44	0.33
35	0.19	0.33	**0.38**
40	0.19	0.31	0.36
45	**0.23**	0.36	0.31
50	0.20	0.43	0.30
55	0.20	**0.49**	0.24

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 3.4.

T, which is listed in Table 3.4, was not used for calculating f_b, $f_{\mathsf{c_v}}$, $f_{\mathsf{c_a}}$, or $f_{\mathsf{c_j}}$, because all of the data was used to calculate these features. The correlation coefficients for f_b, $f_{\mathsf{c_v}}$, $f_{\mathsf{c_a}}$, and $f_{\mathsf{c_j}}$ were 0.26, 0.33, 0.43, and 0.46, respectively. These features are then used to predict the aggressiveness of driving behavior using multiple linear regression. For f_s, f_a, and f_v, 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. 3.3–3.9.

From the results, compared with the features of other driving behaviors, abrupt steering (f_s) 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 access was restricted to the recorded video data. On the other hand, the features of acceleration behavior (f_{a}), i.e., acceleration from a stop, and alternation behavior ($f_{\mathrm{c_j}}$) i.e., standard deviation of jerk, showed relatively high correlation coefficients (about 0.5) in relation to the consultants' aggressiveness scores.

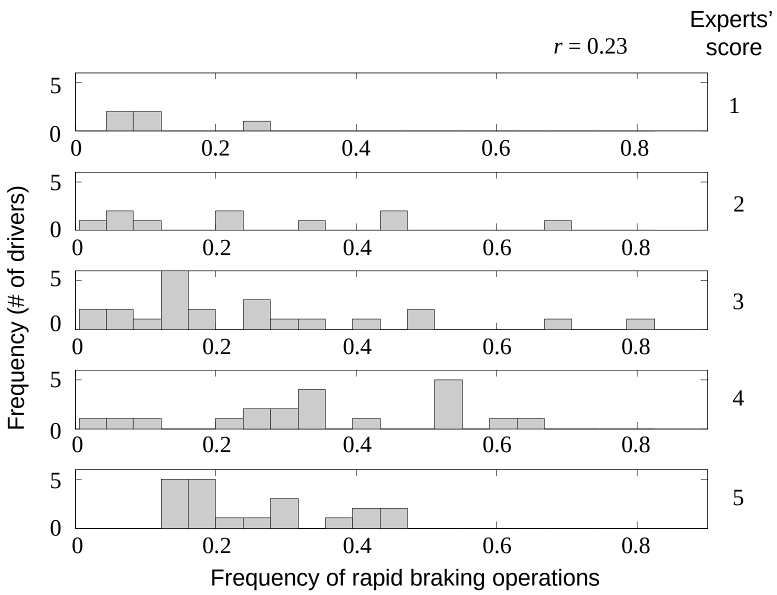

Figure 3.3: Relationship between f_{s} and corresponding empirical scores given by risk consultants. Correlation coefficient was $r = 0.23$ when $T = 45$ [sec].

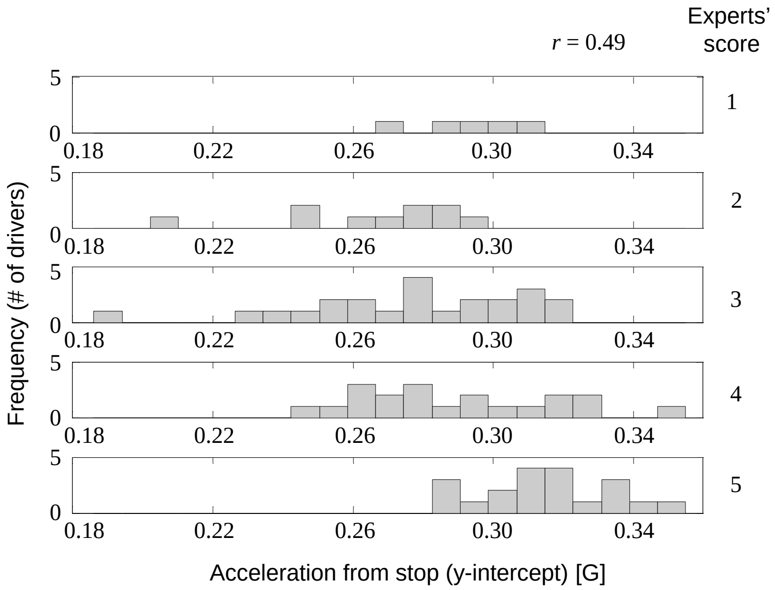

Figure 3.4: Relationship between f_{a} and corresponding empirical scores given by risk consultants. Correlation coefficient was $r = 0.49$ when $T = 55$ [sec].

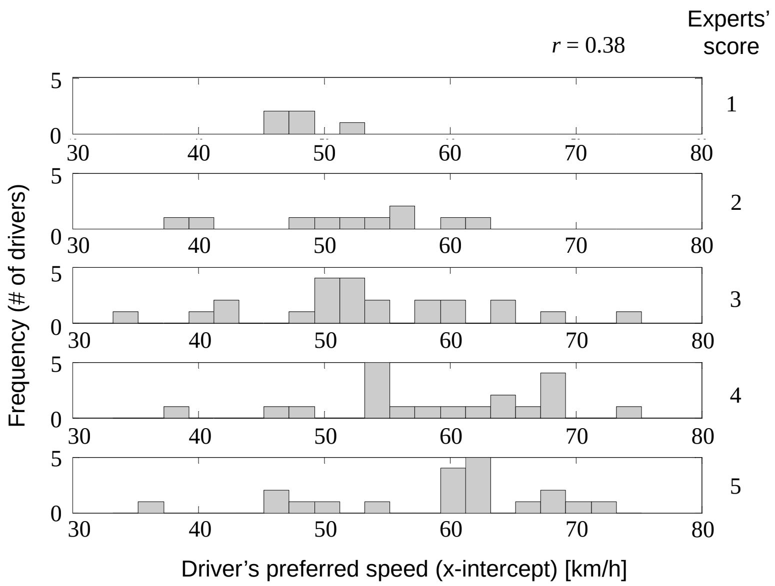

Figure 3.5: Relationship between f_{v} and corresponding empirical scores given by risk consultants. Correlation coefficient was $r = 0.38$ when $T = 35$ [sec].

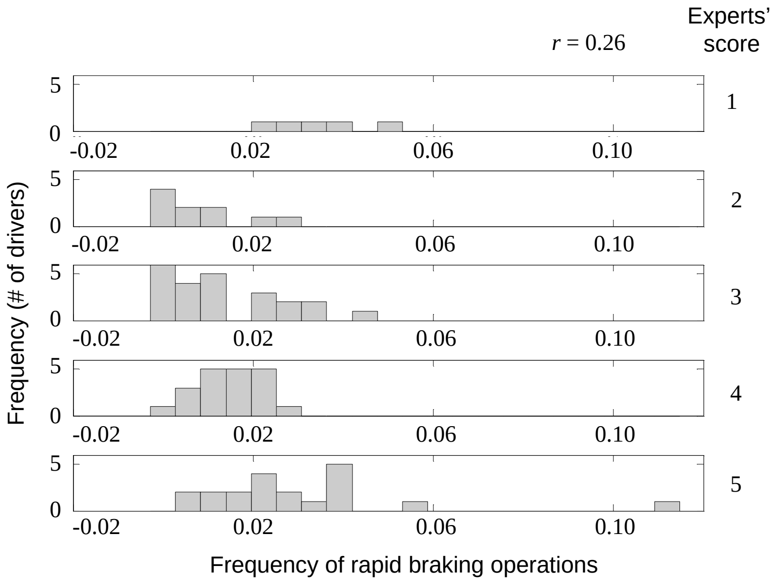

Figure 3.6: Relationship between f_{b} and corresponding empirical scores given by risk consultants. Correlation coefficient was $r = 0.26$.

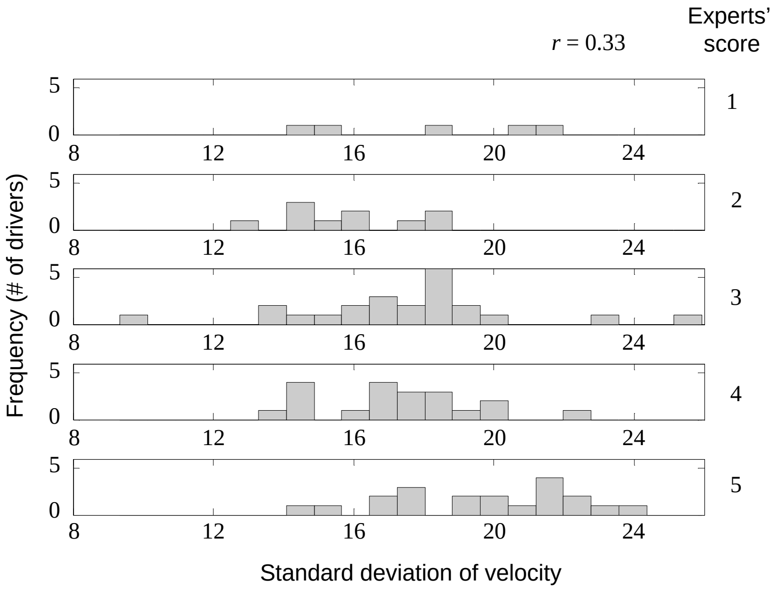

Figure 3.7: Relationship between $f_{\mathrm{c_j}}$ and corresponding empirical scores given by risk consultants. Correlation coefficient was $r = 0.33$.

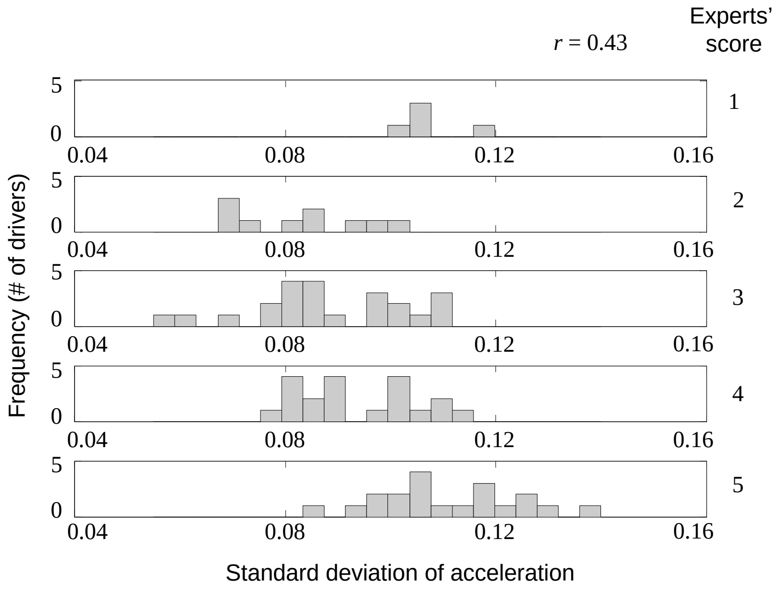

Figure 3.8: Relationship between f_{c_a} and corresponding empirical scores given by risk consultants. Correlation coefficient was $r = 0.43$.

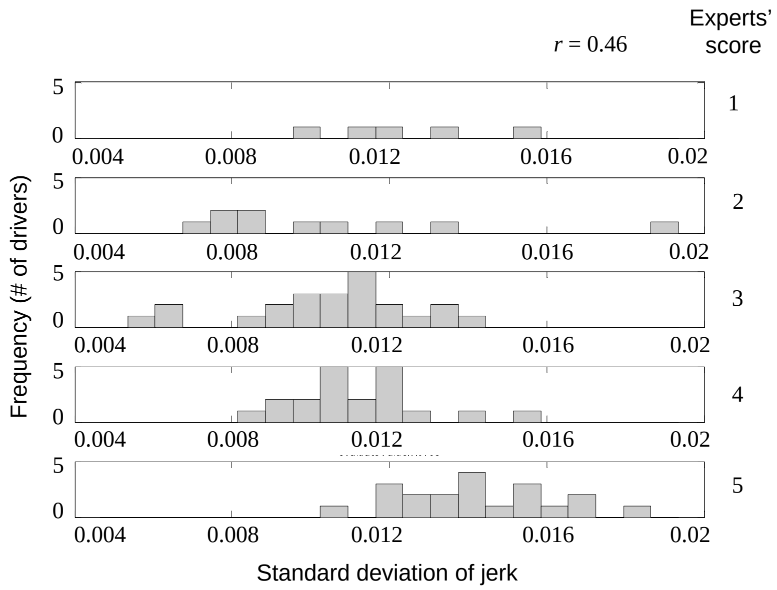

Figure 3.9: Relationship between f_{c_v} and corresponding empirical scores given by risk consultants. Correlation coefficient was $r = 0.46$.

3.4.3 PCA of features

Correlation coefficients of the relationships among features of the various driving behaviors is shown in Table 3.5. We can see that these features are not completely independent of each other, and that in fact some of the features even have relatively strong correlations. The correlation coefficient between f_{s} (proportion of abrupt steering operations) and f_{v} (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 $f_{\mathsf{c_a}}$ (standard deviation of longitudinal acceleration) and $f_{\mathsf{c_j}}$ (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 $f_{\mathsf{c_v}}$, $f_{\mathsf{c_a}}$, and $f_{\mathsf{c_j}}$, 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 $f_{\mathsf{c_v}}$, $f_{\mathsf{c_a}}$, and $f_{\mathsf{c_j}}$, e.g., the correlation coefficient between $f_{\mathsf{c_a}}$ and $f_{\mathsf{c_j}}$ is 0.76. All three of these features represent characteristics of alternation behavior between acceleration and deceleration. These correlations between specific driving behaviors, i.e., steering behavior, acceleration behavior, deceleration behavior, and alternation behavior, indicate that it is difficult to separate driving behavior into independent sub-behaviors. Therefore, PCA has been decided to be applied to the features of each behavior prior to performing linear regression.

Table 3.5: Correlations between driving behavior features.

Feature	f_s	f_a	f_v	f_b	$f_{\mathrm{c_v}}$	$f_{\mathrm{c_a}}$	$f_{\mathrm{c_j}}$
f_s	1.00	–	–	–	–	–	–
f_a	−0.29	1.00	–	–	–	–	–
f_v	0.57	−0.16	1.00	–	–	–	–
f_b	−0.34	0.35	0.10	1.00	–	–	–
$f_{\mathrm{c_v}}$	−0.34	0.31	0.29	0.50	1.00	–	–
$f_{\mathrm{c_a}}$	−0.52	0.67	−0.08	0.79	0.58	1.00	–
$f_{\mathrm{c_j}}$	−0.45	0.55	−0.02	0.57	0.31	0.76	1.00

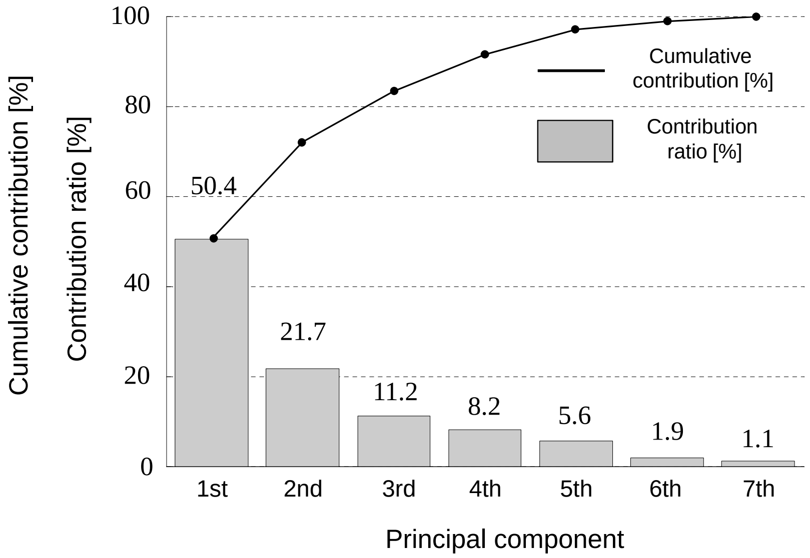

Figure 3.10: Contribution ratio of each principal component and their cumulative curve.

Contribution ratios of each principal component and their cumulative curves are shown in Fig. 3.10. 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, the first principal component was found to be mainly related to the riskiness of acceleration and deceleration behavior, and the second principal component was found 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.

3.4.4 Aggressiveness prediction using MLR and PCR

The aggressiveness of each driver's behavior was predicted using Eq. (3.1), employing both multiple linear regression (MLR) and principal component regression (PCR). The leave-one-out method was employed, i.e., the driving data from 77 drivers were used to estimate the regression coefficients for the remaining (target) driver. An hundred twenty and eight kinds of feature sets (one for MLR and 127 combinations for PCR) were used to estimate the aggressiveness of the drivers' behavior. To evaluate the results of each feature set, Spearman's rank correlation coefficient and root mean square error (RMSE) between the empirical scores given by the risk consulting experts and the aggressiveness scores assigned using the proposed method, were calculated.

Correlation coefficient

Table 3.6 shows feature sets used for driving aggressiveness prediction and their rank correlation coefficients between the predicted aggressiveness scores using the proposed method and the empirical scores given by risk consulting experts. **ALL** used all of the features extracted from the driving behaviors to estimate regression coefficients directly using MLR. $\mathbf{P}_i$ indicates the feature sets for PCR which employed combinations of i principal components to estimate regression

Table 3.6: 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**	f_{s}, f_{a}, f_{v}, f_{b}, $f_{\mathrm{c_v}}$, $f_{\mathrm{c_a}}$, $f_{\mathrm{c_j}}$	100	0.64
PCR	$\mathbf{P}_1$	2nd principal component	21.7	0.38
	$\mathbf{P}_2$	2nd and 3rd principal components	32.9	0.54
	$\mathbf{P}_3$	1st–3rd principal components	83.3	0.67
	$\mathbf{P}_4$	1st–4th principal components	91.5	0.74
	$\mathbf{P}_5$	1st–4th, 6th principal components	93.4	0.67
	$\mathbf{P}_6$	1st–4th, 6th, 7th principal components	94.5	0.66
	$\mathbf{P}_7$	1st-7th principal components	100	0.64

coefficients. For those feature sets using the same number of principal components, only the one with highest correlation coefficient is listed in Table 3.6.

We can see in Table 3.6 that correlation coefficients vary from 0.38 to 0.74, and that the highest correlation coefficient was obtained using feature set $\mathbf{P}_4$, which employed the first four principal components. All seven principal components were employed in $\mathbf{P}_7$, with a resulting correlation coefficient of 0.64, which was the same as **ALL**. Results using **ALL** (MCR) and $\mathbf{P}_4$ (PCR) are shown in Figs. 3.11 and 3.12, respectively.

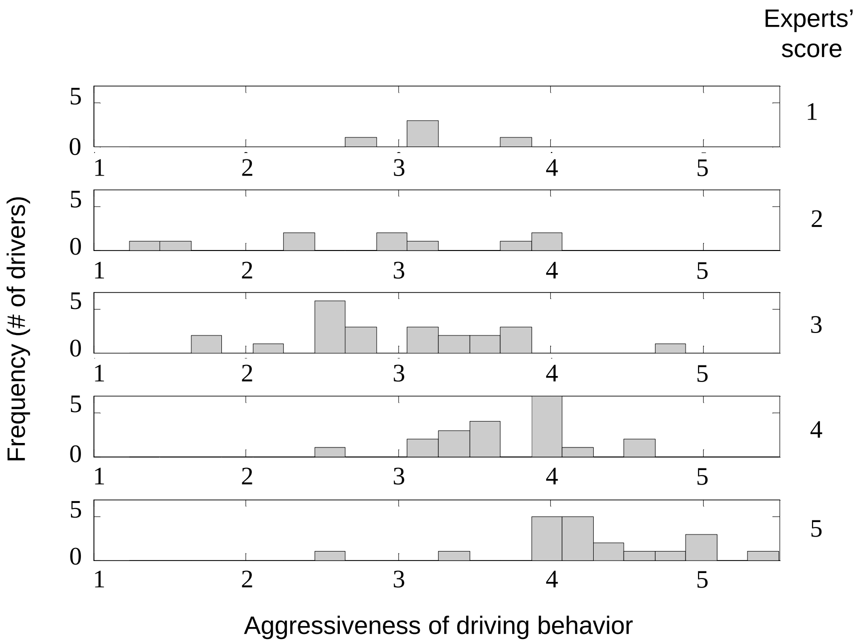

Figure 3.11: Correlation between empirical scores given by risk consultants and automated aggressiveness scores, using MLR with all features (**ALL**). Correlation coefficient was $r = 0.64$.

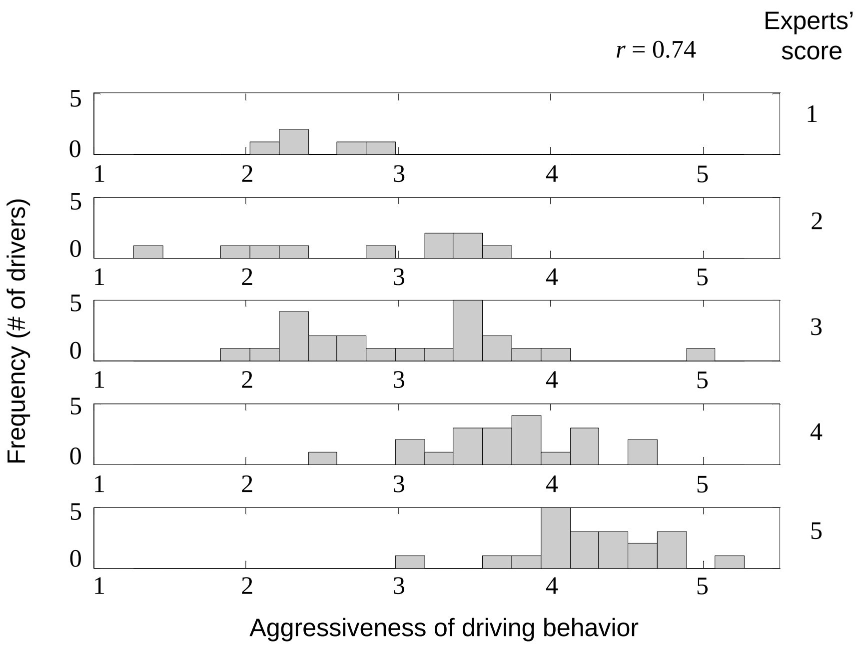

Figure 3.12: Correlation between empirical scores given by risk consultants and automated aggressiveness scores, using PCR with first four principal components ($\mathbf{P}_4$). Correlation coefficient was $r = 0.74$.

Table 3.7: Regression coefficients for **ALL** and $\mathbf{P}_4$.

Feature set	α_0	α_1	α_2	α_3	α_4	α_5	α_6	α_7
ALL	3.51	0.50	0.25	0.21	–0.35	0.19	0.48	0.33
$\mathbf{P}_4$	3.51	0.23	0.37	0.49	0.20	–	–	–

In both of these figures, correlations between the experts' scores and the predicted aggressiveness scores can be observed, with correlation coefficients of 0.64 (**ALL**) and 0.74 ($\mathbf{P}_4$), 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 $\mathbf{P}_4$ are shown in Table 3.7. Since the aggressiveness scores of 78 drivers was predicted 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 3.7 shows $\{\alpha_i\}$ calculated using the data of all 78 drivers. When **ALL** was employed, regression coefficient α_4, which corresponds to risky frequency of braking operations, became negative. This is difficult to understand, but it may have been caused by multi-collinearity [64].

Prediction error

Figure 3.13 shows the root-mean-square error (RMSE) of the predicted aggressiveness scores by the proposed method 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 $\mathbf{P}_4$, with RMSE increasing to 0.99 for **ALL** and $\mathbf{P}_7$, and 1.92 for **RANDOM**.

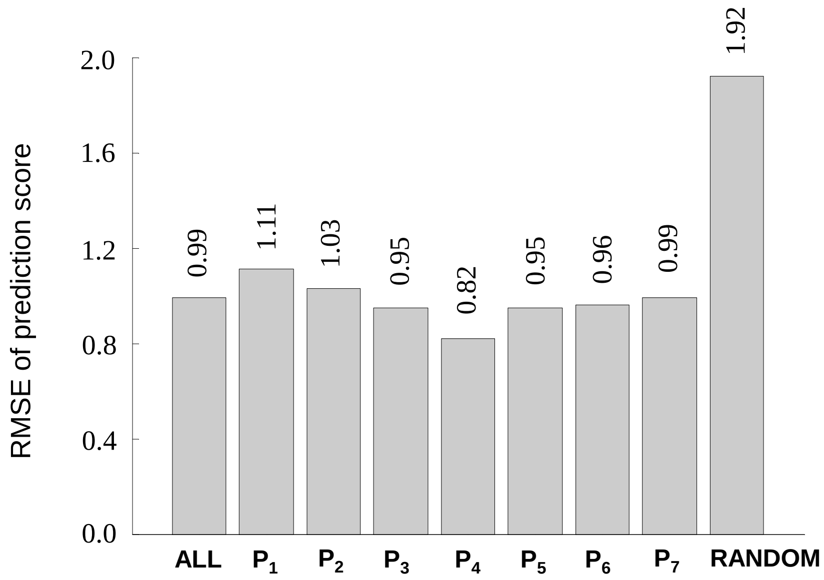

Figure 3.13: Root mean square errors (RMSE) of automated scores obtained by feature sets in Table 3.6 and **RANDOM**.

3.5 Conclusion of the chapter

A technique for measuring the aggressiveness of driving behavior was proposed in this chapter, based on the use of driving behavior signals and principal component regression. Aggressiveness was assumed that it could be measured by analyzing four types of driving behavior; steering behavior, acceleration behavior, deceleration behavior, and alternation behavior 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. The proposed method was used to measure the aggressiveness of 78 drivers of corporate vehicles, using driving data collected with drive recorders during real-world driving. Its performance was then evaluated by comparing the proposed aggressiveness scores with the aggressiveness scores given to the same 78 drivers by risk consulting experts. Experimental results showed that the proposed multiple linear regression model achieved a performance correlation coefficient of 0.64 in relation to the empirical evaluations of the risk consulting experts. By applying PCA to the feature sets, the prediction performance was improved and a correlation coefficient of 0.74 was obtained.

The next step in this work is to investigate more effective features for detecting abrupt steering operation. Additional aggressiveness features based on other driving behaviors should also be developed and employed, 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 [65]. 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 [66–68], so we may be able to improve the ability to detect aggressive driving behavior by combining the observation of driving signals with psychological models.

Chapter 4

Integrated Measure for Similarity of Driving Behavior

Keywords in this chapter:

- Driving scene retrieval
- Integrated similarity measure
- Driving behavior
- Driving environment

4.1 Summary of the chapter

This chapter proposes a similarity measurement technique for retrieving similar driving scenes, using driving behavior signals and features of the driving environment. A previous work by Naito et al. proposed a similarity-based retrieval system for finding driving data, which retrieved driving scenes by measuring similarity between scenes using driving behavior signals, such as steering angle and vehicle velocity [47]. However, driving scenes can also be characterized by the surrounding driving environment. Here, driving scenes are assumed to consist of three major entities; the driver, the (driver's) vehicle, and the (driving) environment. The similarity between driving scenes are measured using road features as well as the position and motion of surrounding vehicles (i.e., the surrounding driving environment), in addition to driving behavior signals obtained from the driver and his/her vehicle. A driving scene retrieval experiment is conducted to evaluate the proposed similarity measurement method, using driving data collected on an expressway. Experimental results show that the additional use of environmental information significantly improves the precision of the retrieval of driving scenes that contain certain events compared with a conventional method. According to the results, different people were found to focus on different elements when comparing driving scenes, which may indicate that different drivers would focus on different things when driving.

4.2 Introduction

With the increased presence and recent advances of drive recorders, rich driving data that include video, vehicle acceleration signals, driver speech, GPS data, and several sensor signals can be continuously recorded and stored. These advances enable researchers to study driving behavior more extensively for traffic safety. However, increasing the variety and the amount of driving data complicates finding desired data, e.g. driving scenes that contain similar driving events and behaviors, from large database. To solve these problems, we developed a retrieval system for driving scenes that provides similarity-based retrieval functions. In this research, driving scenes are defined as several specific driving events, which consist of various driving data recorded from both intra-vehicle and surrounding environment synchronously.

Researchers have tried various approaches, such as driving event recognition using stochastic probability methods, to search for desired data. Pentland et al. proposed a method of modeling human behavior using dynamic models with a Markov chain [69]. Using proposed method, an average driving event recognition accuracy rate of 95% was achieved using driving data collected with a driving simulator. Oliver et al. further expanded driving behavior recognition research by using graphical models with data collected from a real driving environment [70]. In some situations, such as passing, their models showed a 100% event recognition accuracy. Mitrovic et al. also proposed a reliable method using Hidden Markov Models for driving event recognition [46]. They reported that their method correctly recognized about 98% of driving events. Using the stochastic probability models described above, previous researchers have achieved very high event recognition performance. However, in all of these studies, models corresponding to various driving events needed to be trained in advance.

Instead of using a probabilistic method, while developing a driving data retrieval system, Naito et al. employed a time-series active search to retrieve driving events [47, 48]. In contrast with the time-cost of model training when using probabilistic event recognition methods, their method directly measured the similarity between driving data. In their work, driving behavior signals, which can also be called intra-vehicle driving signals (e.g., velocity and steering angle), were employed as feature vectors. Similar driving data was then retrieved by comparing differences in the histograms of the quantized vectors. According

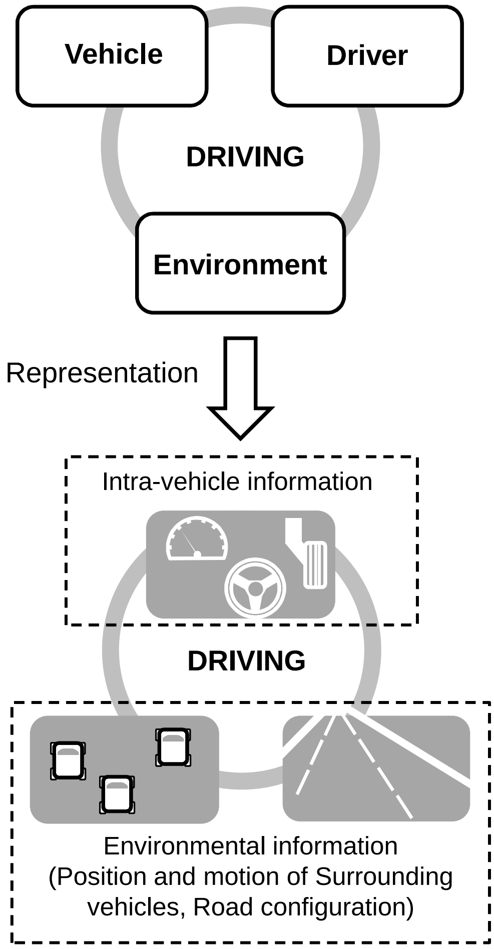

Figure 4.1: Three major entities of driving. Driving can be described as the interaction of three major entities; the driver, the vehicle, and the environment. In this chapter, driving is represented by intra-vehicle information and environmental information.

to experimental results, a retrieval accuracy of more than 97% was achieved for scenes of driving on curves. However, driving signals from the surrounding environment, such as features of the road or information about surrounding vehicles, were not employed, which meant that some driving events could not be retrieved accurately. For example, without information about driving lane position and the relative positions of surrounding vehicles, lane changes cannot be easily differentiated from driving on curves.

Driving is actually a complex decision-making process due to the relationships between the three major entities involved, which include the driver, the vehicle, and the environment, as shown in Fig. 4.1. Information about these entities can be obtained from driving data, such as the driver's behavior, the vehicle's motion, as well as the position and motion of surrounding vehicles and road information. In this chapter, the three major entities are represented by intra-vehicle and environmental information. Based on these two information, a distance measurement technique to retrieve driving events by measuring similarity between driving scenes is proposed. Here, the assumption is that the driver and his/her vehicle are represented as the integration of the driver's behavior and the vehicle's motion, and the environment can be represented by the road and the surrounding vehicle conditions, respectively.

Experiments of driving scene retrieval was conducted to evaluate the proposed method. As an objective evaluation, first, driving event retrieval performance was investigated by comparing the proposed method with other retrieval methods. As a subjective evaluation, correlations between the subjective similarity measures and the measured similarities using several different retrieval methods, including the proposed method, were examined.

The rest of this chapter is organized as follows. Section 4.3 introduces the recorded driving data used in this research. In Section 4.4, a technique to measure the similarity between driving scenes is proposed. A driving scene retrieval experiment is presented in Section 4.5. The experimental results are discussed in Section 4.6, and conclusions and future work are presented in Section 4.7.

4.3 Driving data recording

Driving data was collected on a real expressway, and was recorded using the instrumented vehicle shown in Fig. 4.2. It was a subset of a driving database [16]

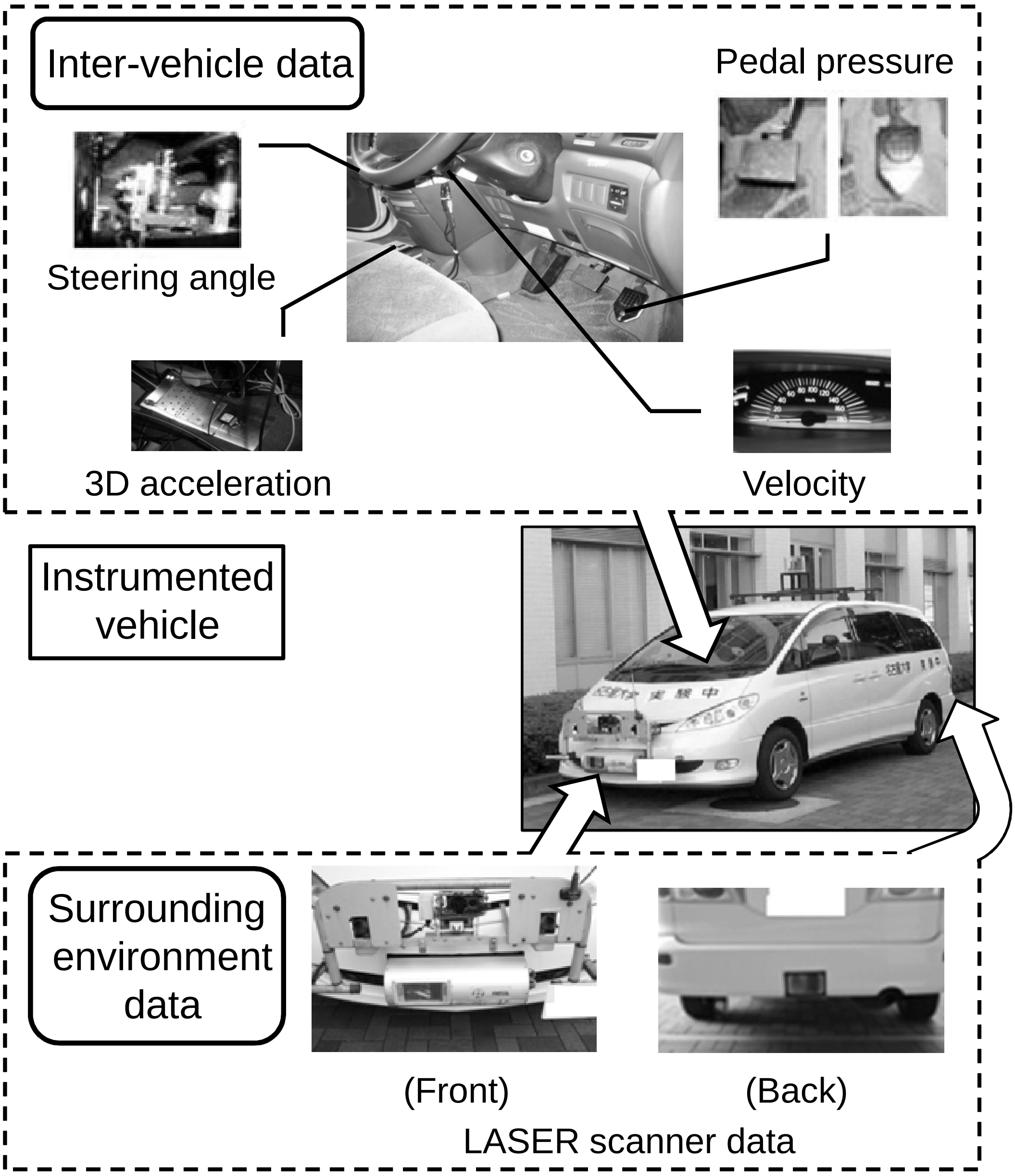

Figure 4.2: Instrumented vehicle used for driving data collection, which allows synchronous recording of all driving data.

recorded from six drivers. For each driver, he/she drives a route with a length of 34.1 [km], with a total duration of approximate one hour. The collected driving behavior signals included velocity [km/h], longitudinal and lateral acceleration [G], gas and brake pedal pressures [N], and steering wheel angle [deg]. To detect surrounding objects in the driving environment, data from two LASER scanners that were mounted on the front and back of the vehicle were employed. Although LASER scanners are currently still expensive, they are expected to be cheaper and easier to be installed in vehicles in the future. Discrete LASER dots from the surrounding objects were clustered using Euclidean distance. According to the geometric features of each cluster, they could be identified as the road or surrounding vehicles [71]. The curvature of each road was calculated in advance. The relative position and velocity of each surrounding vehicle were calculated in relation to the driver's vehicle. The LASER scanners covered 80-degree arcs at both the front and the back of the vehicle, to an effective range of approximately 100 meters to the front and 55 meters to the rear. A Kalman filter [72] was employed to track the motion of vehicles in blind areas [73]. Four cameras recorded video of the road to the front and the side, as well as the driver's feet while driving. All of the driving data were recorded synchronously.

4.4 Similarity measurement between driving scenes

In this section, similarity measurement between driving scenes is proposed. To represent the three major entities of a driving event, driving behavior signals were employed to depict features of the driver and his/her vehicle, and information about the road and surrounding vehicles to depict the most common features of the driving environment. Three similarity measures are prepared, one for each entity. The similarity D is defined as their linear combination as follows.

$$D = \alpha d_{\mathrm{b}} + \beta d_{\mathrm{r}} + (1 - \alpha - \beta) d_{\mathrm{s}}. \tag{4.1}$$

where d_{b} indicates the similarity between driving behavior signals, d_{r} indicates the similarity between road features, and d_{s} indicates the similarity between surrounding vehicles. Each of the three distances was normalized to zero mean and unit variance, and α, β, and $1 - \alpha - \beta$ are their weights, respectively. The three similarity measures ($d_{\mathrm{b}}, d_{\mathrm{r}},$ and d_{s}) and their combination D can be used to measure the similarity between frames at each point in time of driving scenes. To measure the similarity between scenes with different lengths, a Dynamic Time Warping (DTW) algorithm [45] was employed. Conventional Euclidean distance is used for measuring driving behavior signals and road information, and an original distance measure is used to evaluate the similarity of surrounding vehicle information.

4.4.1 Driving behavior signals

The six most common driving signals were employed to represent information about the driver and his/her vehicle (intra-vehicle information), and at each point in time they were used to calculate a feature vector: $\mathbf{o}_{\mathrm{b}} = (v, s, p_{\mathrm{b}}, p_{\mathrm{g}}, a_{\mathrm{y}}, l_{\mathrm{x}})^{\mathrm{T}}$, where v indicates vehicle velocity, s indicates steering angle, p_{b} indicates brake pedal pressure, p_{g} indicates gas pedal pressure, a_{y} indicates longitudinal acceleration, and l_{x} indicates lateral acceleration, respectively. The Euclidean distance between the feature vectors was used as similarity d_{b} for measuring the distance between the driving scene frames.

4.4.2 Road features

Road features acquired from LASER scanner data were employed to represent part of the driving environment information. Road curvature and relative position of the driver's vehicle on the roadway, as the most obvious road features, were selected. A feature vector at each point in time consists of six features: $\mathbf{o}_\mathrm{r} = (c_\mathtt{f}, c_\mathtt{b}, f_\mathtt{r}, f_\mathtt{l}, b_\mathtt{r}, b_\mathtt{l})^\mathrm{T}$, where $c_\mathtt{f}$ and $c_\mathtt{b}$ indicate the curvature of the road, in front of and in back of the driver's vehicle, respectively. $f_\mathtt{r}$, $f_\mathtt{l}$, $b_\mathtt{r}$, and $b_\mathtt{l}$ indicate the relative positions of roadside barriers, on the front right, front left, back right and back left of the driver's vehicle, respectively. Again, the Euclidean distance between the road feature vectors was used as similarity $d_\mathtt{r}$ between driving scene frames.

4.4.3 Surrounding vehicle information

Features of surrounding vehicles were employed to provide additional environmental information about driving scenes. The distance between these features is defined as:

$$d_\mathtt{s} = \frac{\displaystyle\sum_{(V_1,V_2)\in M} \left| w_{V_1} - w_{V_2} \right| + \sum_{V_1 \in U_1} w_{V_1} + \sum_{V_2 \in U_2} w_{V_2}}{\displaystyle\sum_{V_1 \in F_1} w_{V_1} + \sum_{V_2 \in F_2} w_{V_2}}, \tag{4.2}$$

where F_1 and F_2 represent sets of frames in which surrounding vehicles are detected by LASER scanners, V_1 and V_2 indicate surrounding vehicles which belong to F_1 and F_2, respectively. (V_1, V_2) indicates that V_1 and V_2 are a matched pair of vehicles, and M is a set of matched pairs of vehicles between F_1 and F_2. U_1 and U_2 are sets of vehicles in F_1 and F_2, respectively, which have no matching vehicles. The matched pairs of vehicles were found using Euclidean distance and Weber's Law [74].

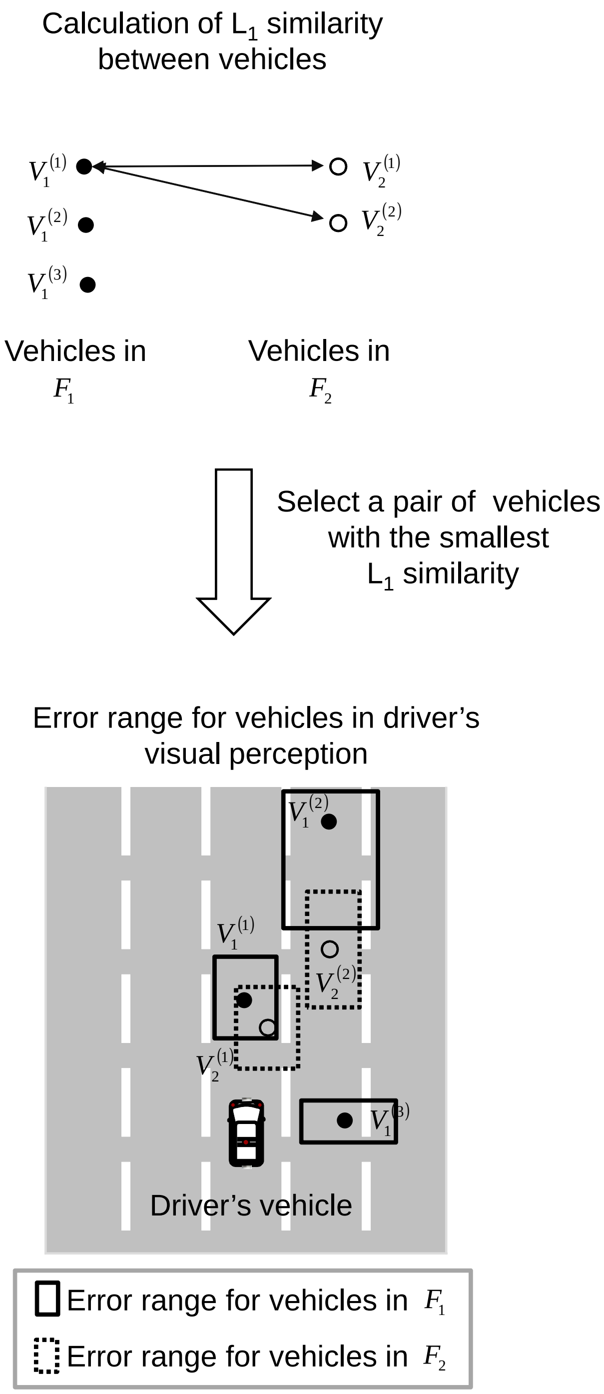

Figure 4.3: Process for vehicle matching. Whether two vehicles match or not is based on $\mathtt{L}_1$ similarity between them (top) and their error ranges in driver's visual perception (bottom).

The process for vehicle matching is shown in Fig. 4.3. Each surrounding vehicle was represented as a feature vector: $\mathbf{o}_\mathrm{s} = (x, y, v_\mathrm{x}, v_\mathrm{y})^\mathrm{T}$, where x and v_x indicate the relative position of a surrounding vehicle and its velocity in relation to the driver's vehicle in a lateral direction, respectively, and y and v_y indicate the relative position of a surrounding vehicle and its velocity in relation to the driver's vehicle in a longitudinal direction, respectively. For each surrounding vehicle in F_1, e.g. $V_1^{(1)}$, the Euclidean distance was calculated between the feature vector of $V_1^{(1)}$ and the feature vector of every surrounding vehicle in F_2. The vehicle in F_2 with smallest distance to $V_1^{(1)}$ was selected as $V_2^{(1)}$. Then, as shown on the right of Fig. 4.3, error ranges for $V_1^{(1)}$ and $V_2^{(1)}$, respectively, were used to represent error in the driver's visual perception. According to Weber's law, as a vehicle moves further from the driver's vehicle, the error range becomes larger. Only if $V_1^{(1)}$ is inside the range of $V_2^{(1)}$, and $V_2^{(1)}$ is also inside the range of $V_1^{(1)}$, are these two vehicles considered to be matched.

In Equation (4.3), w_V is the weight of surrounding vehicle V, to indicate its importance to the driver. Here, the assumption is that surrounding vehicles closer to the driver's vehicle are more important than those further away. Moreover, at point t in time, the importance of vehicle $w_V^{(t)}$ depends on whether it is just being noticed or if it was previously noticed by the driver. In the case where it was previously noticed, its importance also depends on its relative velocity and position in the longitudinal direction, in relation to the driver's vehicle at point t

in time. $w_V^{(t)}$ is defined as:

$$
w_V^{(t)} = \begin{cases} \dfrac{1}{|x|^{(t)} + |y|^{(t)}}, & \text{if} \left\{ \sum_{i=1}^{t-1} \delta(m,1)^{(i)} > 0 \right\} \wedge \left\{ (v_{\mathrm{y}}^{(t)} > 0) \vee (y^{(t)} > 0) \right\} \\ \dfrac{\delta(m,1)^{(t)}}{|x|^{(t)} + |y|^{(t)}}, & \text{otherwise} \end{cases} \tag{4.3}
$$

where $\delta(m, 1)$ is Kronecker's delta, where $m = 1$ (i.e. $\delta(1, 1) = 1$), which indicates that a surrounding vehicle was of concern to the driver. The assumption is that vehicles were of concern to the driver as long as they were located in the direction of the driver's gaze. In the following experiment, an annotator manually labeled the driver's gaze direction frame by frame, by watching recorded video of the driver's face. Since research on driver gaze tracking has been widely reported [75, 76], an automatic gaze tracker could be used for labeling driver's gaze direction in future work, but it is out of scope of this study.

4.5 Experiment

A driving scene retrieval experiment was calculated to evaluate the proposed distance measurement technique. In this experiment, driving scenes were divided manually into five kinds of driving events; driving straight ahead, driving on curves to the left and the right, and lane changes to the left and the right. The experiment itself consists of two parts: 1. Weights for the three distance measures (α and β) were estimated for each subject, 2. Retrieval performance of various retrieval methods with different similarity measures was compared objectively and subjectively.

4.5.1 Weight estimation for the three similarity measures

In Section 4.5.2 subjective similarity scores rated by eleven subjects (three males and eight females) will be used to evaluate the similarity of the retrieved driving scenes. Before this the best weight values (α, β, and $1 - \alpha - \beta$) for each of the eleven subjects are estimated in this section. On average, the eleven subjects had held a driver's license for 27 years, and drove 11 hours per week.

To estimate the weights (α, β, and $1 - \alpha - \beta$) for each subject, 200 pairs of driving scenes were randomly selected from the recorded data. To collect the subjective similarity scores for each pair of driving scenes, an evaluation system was developed, which is shown in Fig. 4.4. This interface allowed the subjects to simultaneously display synchronously recorded video of the road to the front and the side, as well as the video of the driver's face and feet. They were instructed to imagine that they were driving under the same conditions as driving scenes shown in the system. Each subject was asked to offer his/her subjective score to indicate the similarity level of the contents of each pair of driving scenes, based on four criteria; behavior of the driver and the driver's vehicle (s_{b}), type of road (s_{r}), surrounding vehicles (s_{v}), and overall similarity (S). The subjective similarity scores ranged from 1 to 5, with 1 indicating complete dissimilarity and 5 indicating high similarity. Using these subjective scores, the following equation was minimized with regard to α and β:

$$E(\alpha,\beta) = \sum_{n=1}^{N} \left\{ \alpha s_{\mathrm{b}}^{(n)} + \beta s_{\mathrm{r}}^{(n)} + (1 - \alpha - \beta) s_{\mathrm{v}}^{(n)} - S^{(n)} \right\}^2 , \tag{4.4}$$

with an interval of 0.01. Here, $N = 200$ is the total number of scene pairs. Values for α and β which corresponded to the minimum E were selected for each subject, and are shown in Table 4.1. From this table, it is clear that the weights

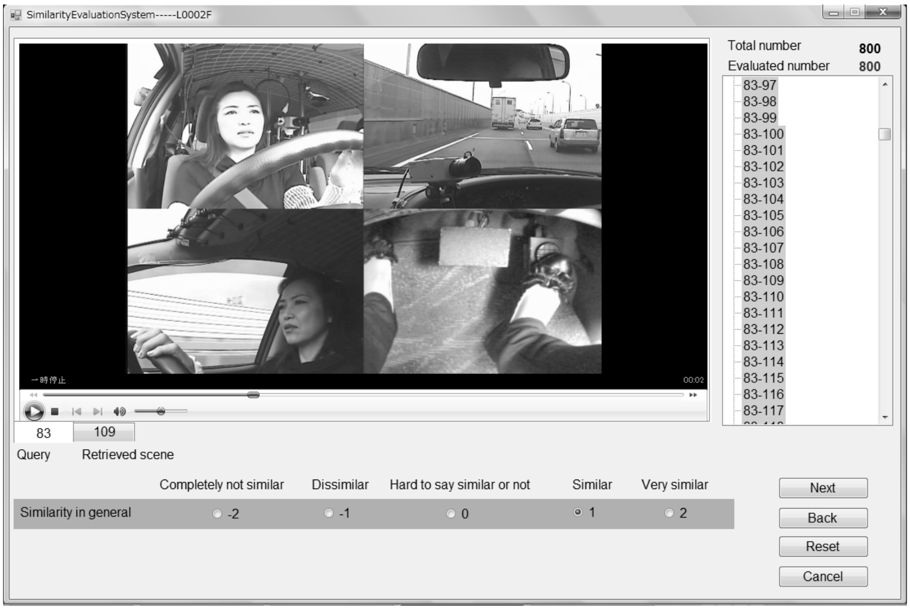

Figure 4.4: Interface for evaluating the retrieved driving scenes. The query and retrieved scenes are simultaneously displayed. Each pair of query and retrieved scenes is shown in the list to the right. The subjects can use buttons (below right) to review any evaluated pair.

(α, β, and $1-\alpha-\beta$) vary widely among subjects. To test whether the variation of weights for the three distance measures is significant, a *t*-test of the weight values for each two groupings of the three entities was performed. The results did not show a significant difference at a significance level of 0.05, which may indicate that, on average, the three driving entities share the same importance. However, individual subjects may have focused on different elements of the driving scenes. Some of the subjects may have thought that objects in the surrounding environment were much more important, such as subject L0008M, for example, while other subjects, such as L0010F, may have thought the driver, the vehicle and the driving environment had almost equal importance.

Table 4.1: Driving situation weights for each subject.

Subject ID	α	β	$1-\alpha-\beta$
L0002F	0.42	0.29	0.29
L0003M	0.32	0.51	0.17
L0004F	0.35	0.37	0.28
L0005M	0.36	0.29	0.35
L0006F	0.33	0.42	0.25
L0008M	0.27	0.13	0.60
L0010F	0.26	0.44	0.30
L0011F	0.35	0.35	0.30
L0012F	0.22	0.66	0.12
L0013F	0.27	0.52	0.21
L0014F	0.26	0.45	0.29
Mean	0.31	0.40	0.29

4.5.2 Driving scene retrieval

Eight retrieval methods with different similarity measures (**A–H**) were employed, which included the proposed methods (**F** and **G**) and also a conventional method **A** [42]. The type of information used by each method is shown in Table 4.2. The difference between methods **F** and **G** is that, method **F** uses equal weights for the three measures (driver's behavior, road, and surrounding vehicles), whereas method **G** uses subject-dependent weights for the three measures, as shown in Table 4.1, which was determined in a subjective evaluation experiment in Section 4.5.1. In the latter section, we will show that method **G** can be employed to retrieve similar scenes of driving behavior for individual drivers' personality. However, the retrieval cannot be fully automated, because parameters α, β, and $1 - \alpha - \beta$ have to be estimated subjectively in this method. The eight methods were used to retrieve driving scenes with of four kinds of common driving events; driving on curves to the left and the right, and changing lanes to the left

Table 4.2: Methods employed for driving scenes retrieval.

Retrieval method	Information used for similarity measurement
A	Histogram of driving behavior signals (Conventional method [42])
B	Driving behavior signals
C	Road information
D	Surrounding vehicle information
E	Surrounding vehicle information (Weight of each surrounding vehicle depends on the direction of the driver's gaze)
F	Information for each of the three major driving entities (α and β both equal to $1/3$)
G	Information for each of the three major driving entities (α and β vary subjectively)
H	Random selection of retrieval results

and the right. There were five, randomly-selected queries for each kind of driving event. For each query, the top five retrieved driving scenes with highest similarities were used for the retrieval performance evaluation. To evaluate the retrieval performance, objective and subjective evaluation experiments were conducted.

Objective evaluation

First, as an objective evaluation, the retrieval precision for the four kinds of driving events was examined, where the retrieval was assumed to be successful if the query and a retrieved scene were of the same type of driving event.

The result of the driving event retrieval experiment is shown in Fig. 4.5. Assuming that the rank of the retrieved events indicates the objective retrieval performance, mean reciprocal rank (MRR) [77] was employed to evaluate the retrieval precision of the top five scenes for each retrieval method. It was shown that

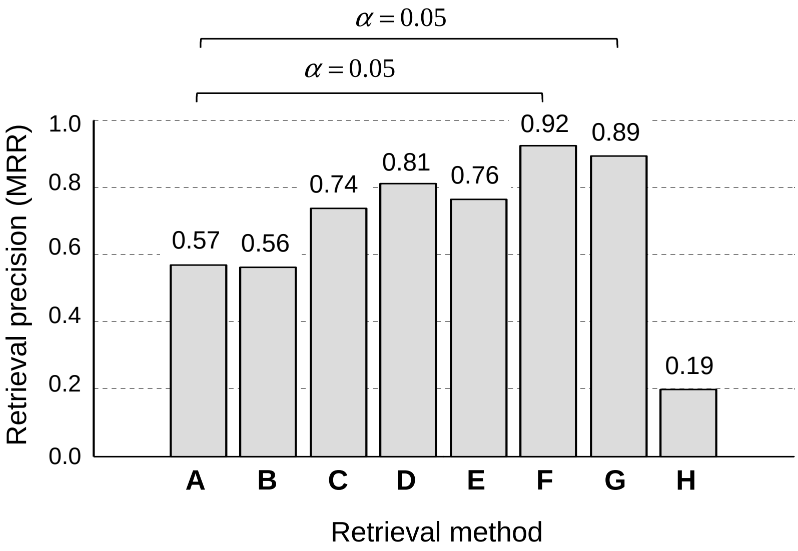

Figure 4.5: Driving event retrieval precision for each retrieval method. Mean reciprocal rank (MRR) was employed for evaluation.

method **F** achieved better performance than the other retrieval methods.

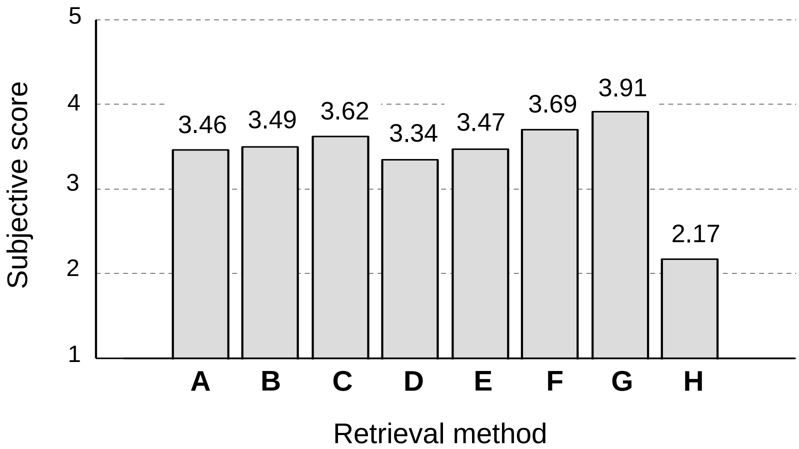

Figure 4.6: Average subjective scores for each retrieval method. Subjective score was used to indicate similarity between retrieved scenes. The average of the given subjective scores from each subject was calculated. Then for each retrieval method, the average subjective score from all the subjects was calculated to indicate the retrieval performance of the method.

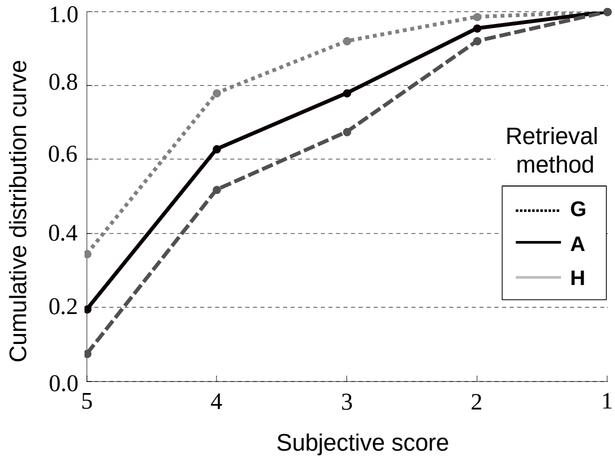

Figure 4.7: Cumulative distribution curves for retrieval methods **G**, **A**, and **H**. For each method, the AUC was 2.96 (**A**), 3.05 (**B**), 3.12 (**C**), 3.01 (**D**), 3.04 (**E**), 3.14 (**F**), 3.36 (**G**), and 2.65 (**H**).

Subjective evaluation

Then, as a subjective evaluation, retrieval performance was evaluated based on subjective similarity scores. Each subject evaluated the similarity of contents of each retrieved scene with the query, and assigned a score of 1−5. After they finished, they were asked to reconfirm their evaluations. The results of the subjective evaluation are shown in Fig. 4.6. To illustrate the precision of each retrieval method in retrieving the top five similar driving scenes, cumulative distribution curves (CDC) was employed, which are shown in Fig. 4.7. Area under the curve (AUC) was also calculated (a higher AUC corresponds to better performance). Results of retrieval performance based on subjective evaluation are shown in Fig. 4.8, where accurate retrieval is defined as retrievals whose subjective similarity scores were 4 or 5. From Figs. 4.6, 4.7, and 4.8, we can see that method **G** with different weights for each subject achieved the best performance.

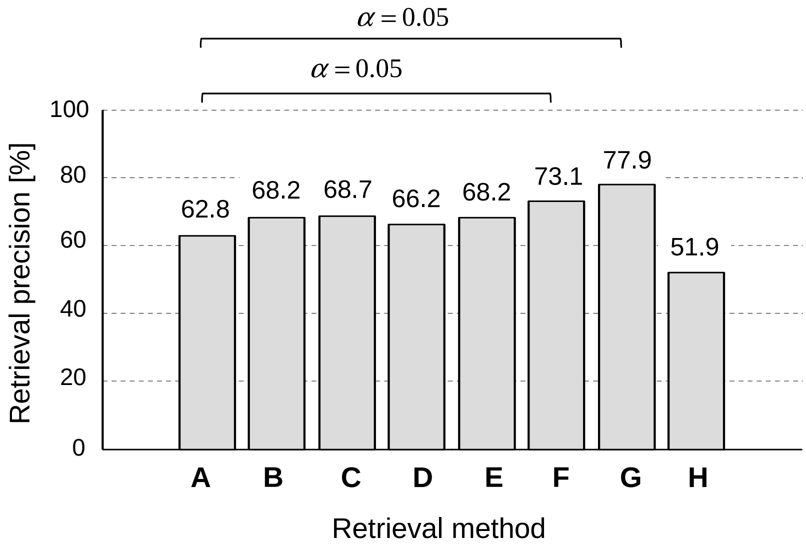

Figure 4.8: Retrieval precision measured with subjective scores. Retrieval precision for each retrieval method is defined as the proportion of accurate retrievals in the retrieved results. Accurate retrieval is defined as that whose subjective similarity scores was 4 or 5.

4.6 Discussion

In this section, the experimental results in Section 4.5 is discussed in regards to the retrieval performance and the individual characteristics of drivers.

4.6.1 Retrieval performance for different methods

First, the retrieval performance of conventional method **A** and the proposed methods **F** and **G** are compared. In both the objective and subjective evaluations, random selection method **H** achieved the lowest retrieval precision. In the objective evaluation (Fig. 4.5), the proposed integrated similarities **F** and **G** achieved significantly higher retrieval precision than conventional method **A**, or methods **B**–**E**, with a significance level of 0.05. Method **B** showed almost the same retrieval performance as conventional method **A**, because both of them employed exactly the same driving behavior signals. In the subjective evaluation (Fig. 4.8), methods **B**–**E**, which used a single driving element, did not show a significant difference in retrieval performance from conventional method **A**. However, the proposed methods **F** and **G**, which focused on all three elements of driving, achieved significantly improved retrieval performance compared to methods **A**–**E**, with a significance level of 0.05.

4.6.2 Retrieval performance for different events

Next, retrieval performance for different driving events is discussed. We can easily see in Fig. 4.9 that retrieval performance for lane change events is much higher than for instances of driving on curves when using retrieval methods **D**, **E**, **F** or **G**. However, retrieval performance was not greatly improved when methods **A**, **B** or **C** were employed. We believe the reason for lower retrieval performance for events involving driving on curves is that lane changes almost always occur on straight roads where there are many surrounding vehicles, and that this additional information about the position and motion of surrounding vehicles provides additional data which benefits retrieval. Information on the position and motion of surrounding vehicles is taken into consideration by retrieval methods **D**, **E**, **F** and **G**. Proposed methods **F** and **G** performed better than the other methods for all types of driving events, because both intra-vehicle and environmental factors are considered when employing these methods. In subjective evaluation, Fig. 4.10 shows similar results with Fig. 4.9. To the eleven subjects, similar lane changes were also more easily to be retrieved than similar driving on curves.

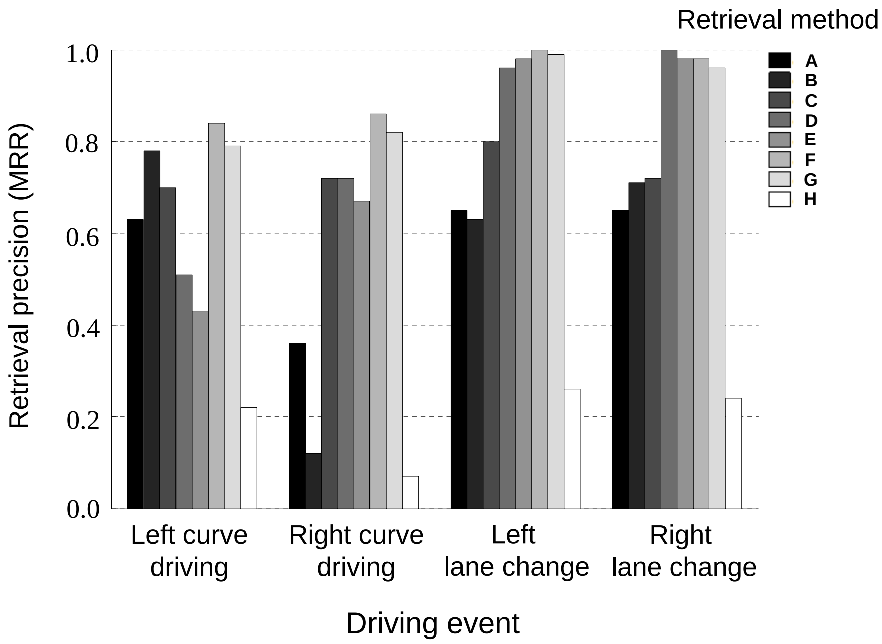

Figure 4.9: Retrieval precision (MRR) for different driving events.

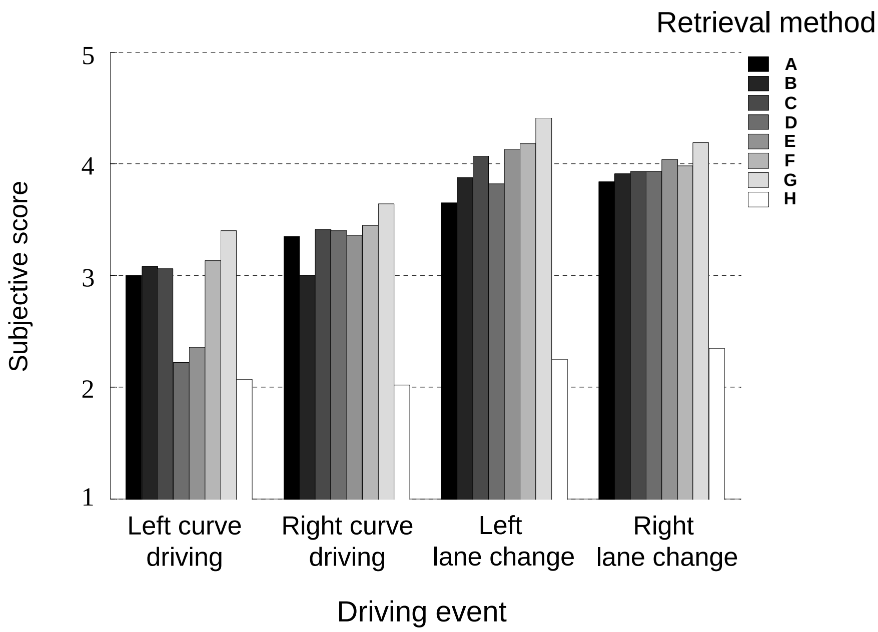

Figure 4.10: Subjective score for different driving events.

4.6.3 Individual characteristics

In the third part, two pairs of retrieval methods are discussed: 1. **D** and **E**, the difference between them being whether or not the weight of each surrounding vehicle depends on the direction of the driver's gaze; and 2. **F** and **G**, where the parameters for α and β were decided by the subjects in **G**, and were set to be equal empirically in **F**. Comparing the precision of the retrieval of driving events (Fig. 4.5) with the precision of the retrieval of similar driving scenes (Fig. 4.8), an interesting phenomena was observed. Although retrieval methods **D** and **F** achieved better driving event retrieval performance than **E** and **G**, respectively, according to subjective confirmation, both **E** and **G** were better at finding similar driving scenes than **D** and **F**, respectively. To clarify the reason for this, Spearman's rank correlation coefficients [63] were calculated for methods **D**, **E**, **F**, and **G**. The correlation coefficients between the subjective scores and the average objective similarities for each method was estimated. The results are shown in Table 4.3, and all results are significant with a significance level of 0.05 [78].

Examples of the relationship between the subjective scores and the objective similarities from the same subjects, using methods **D**, **E**, **F**, and **G**, are shown in Figs. 4.11, 4.12, 4.13, and 4.14, respectively. A descending ladder-like shape, from left to right, indicates a better correlation. According to the results, on average, both **E** and **G** had a higher correlation coefficient than **D** and **F**. To clarify the significance of this differences, a t-test for **E** and **D**, and for **F** and **G** was performed. This revealed that the correlation coefficients of **E** and **G** were significantly different with those of **D** and **F**, respectively, when the significance level is 0.05. These results indicate that retrieval methods **E** and **G** are closer to

Table 4.3: Spearman's rank correlation coefficient for methods **D**, **E**, **F**, and **G** for each subject.

Subject ID	**D**	**E**	**F**	**G**
L0002F	−0.23	−0.68	−0.22	−0.68
L0003M	−0.46	−0.47	−0.23	−0.38
L0004F	−0.27	−0.44	−0.39	−0.36
L0005M	−0.25	−0.57	−0.61	−0.66
L0006F	−0.22	−0.40	−0.17	−0.36
L0008M	−0.11	−0.19	−0.25	−0.75
L0010F	−0.43	−0.55	−0.17	−0.51
L0011F	−0.44	−0.43	−0.34	−0.37
L0012F	−0.35	−0.68	−0.35	−0.62
L0013F	−0.34	−0.33	−0.39	−0.64
L0014F	−0.32	−0.54	−0.33	−0.39
Mean	−0.31	−0.48	−0.31	−0.52

the measured subjective driving similarity values.

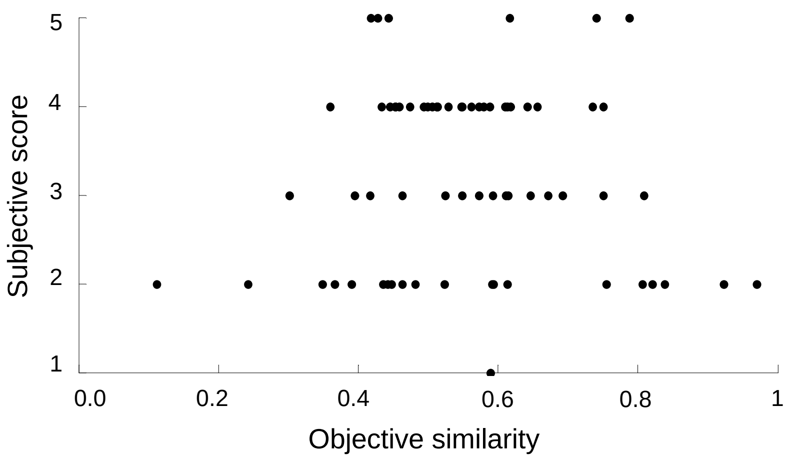

Figure 4.11: Relationship between subjective score and objective similarity for method **D**. Correlation coefficient was −0.23 (subject: L0002F).

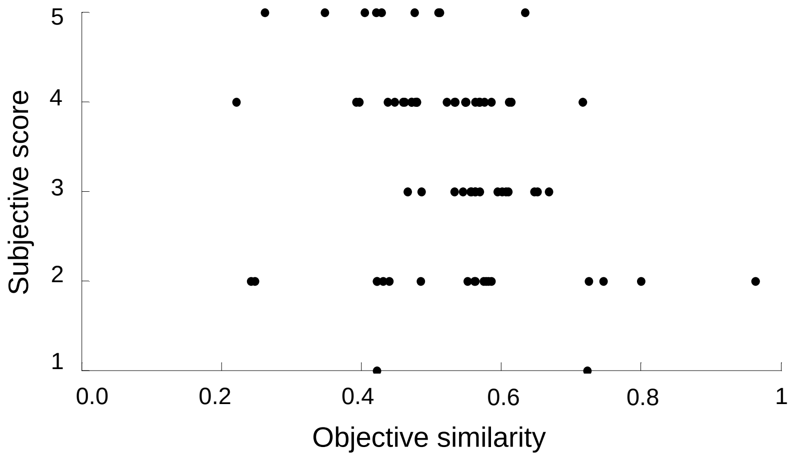

Figure 4.12: Relationship between subjective score and objective similarity for method **E**. Correlation coefficient was −0.46 (subject: L0002F).

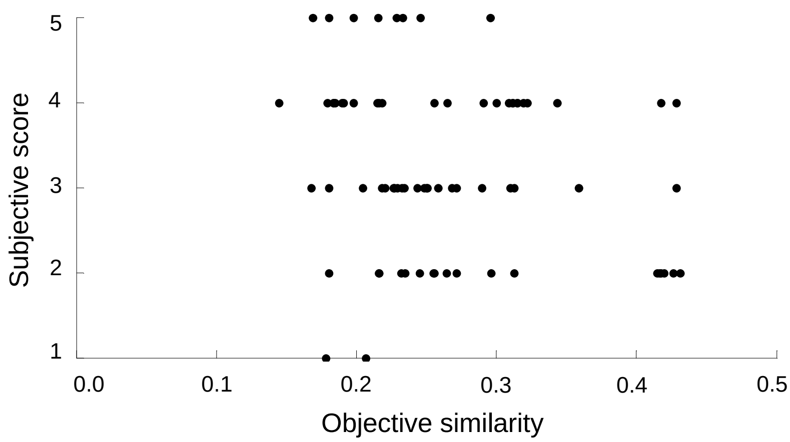

Figure 4.13: Relationship between subjective score and objective similarity for method **F**. Correlation coefficient was −0.25 (subject: L0008M).

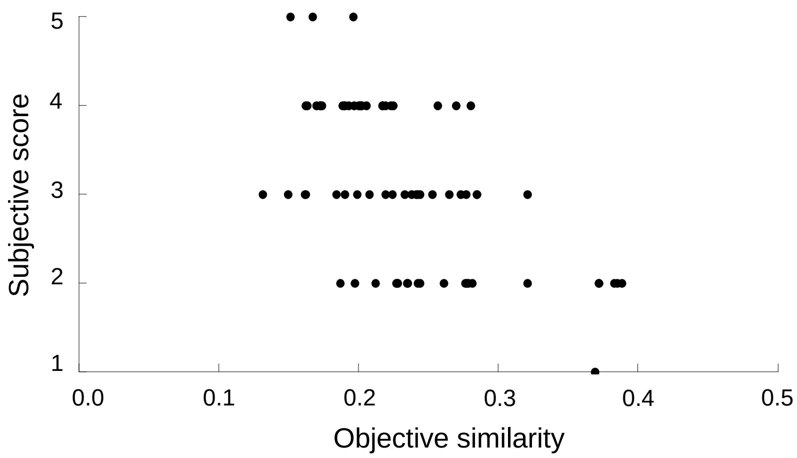

Figure 4.14: Relationship between subjective score and objective similarity for method **G**. Correlation coefficient was -0.75 (subject: L0008M).

In method **E**, it was assumed that only vehicles in the direction of the driver's gaze were being paid attention to by the driver, whereas method **D** supposed that every surrounding vehicle is being equally paid attention to by the driver. The correlation coefficient of method **E** confirmed this assumption that vehicles in the direction of the driver's gaze are considered to be more important. However, less information about surrounding vehicles, as employed in method **E**, may also have led to lower driving event retrieval precision during the objective evaluation, compared with method **D**. Higher correlation coefficients, as in method **E**, indicate that the subjects have similar gaze focus with the drivers in the scenes. On the other hand, even for method **E**, some correlation coefficients were not so high, especially those from L0008M. The reason for this might be that those two subjects had different gaze foci than the drivers in the scenes. A similar conclusion was also mentioned by Mori et al. [79]. In their research, they found that there are individual differences among drivers in gaze direction during driv-

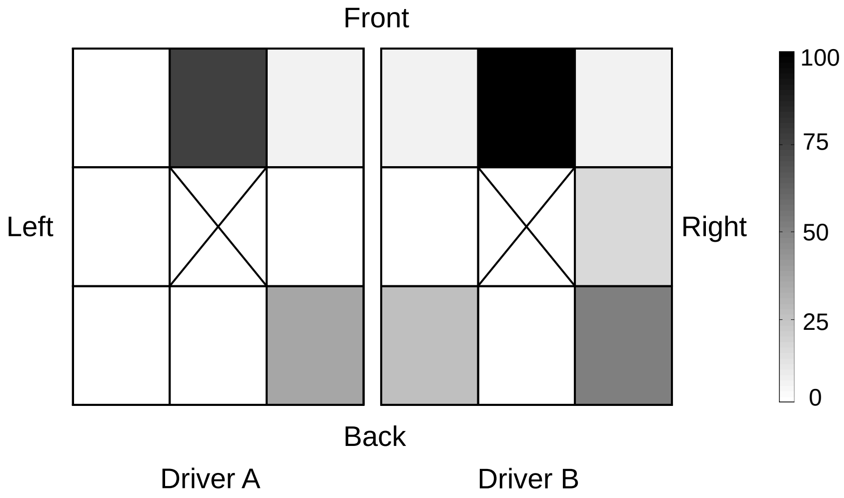

Figure 4.15: Average gaze distribution of drivers A and B during ten right lane changes. Positions of drivers A and B are indicated by the cross at the center of each box. The surrounding boxes represent eight gaze directions during driving. Darker colored boxes represent areas of frequent driver attention, whereas lighter colored boxes indicate directions in which the driver paid little or no attention.

ing. An example of gaze distribution during right lane changes is illustrated in Fig. 4.15. These gaze distributions were calculated using driving data from two drivers among the six drivers in the driving scene retrieval experiment in Section 4.5. It can be seen from this figure that drivers might have had different gaze foci during lane changing.

In method **G**, the weighting of the driver's behavior, road, and surrounding vehicles in driving situations were decided by the subjects who participated in the subjective evaluation experiment. By comparing methods **F** and **G**, it seems that each person compares driving scenes based on their own unique focus. Thus, when we retrieve similar driving scenes for a specific driver, it would be better to use that driver's own similarity evaluations. Moreover, since all of the subjects have been driving for years, they may have developed different foci when observing driver behavior, the position and motion of surrounding vehicles, and road information (all of the three major entities of driving). However, this is a topic which requires further study.

4.7 Conclusion of the chapter

In this chapter, an integrated similarity measurement technique for driving scene retrieval, based on driving behavior, vehicle motion, road type, and the presence of surrounding vehicles, was proposed. Compared with a previous work [42], both the objective and subjective precision of driving scene retrieval were significantly improved. Since there are few studies about driving scene retrieval using driving signals, unfortunately we could not compare the proposed method with more international standard criterion. However, Naito et al. [42] compared their method to a conventional image-based retrieval method that was proposed by Kashino et al. [48] and considered to be an international standard criterion in their experiment. According to the experimental results in [42], retrieval precision for driving behavior improved when driving signals were employed than the image-based method. It was also found that different people focus on different elements of driving scenes when comparing them. Based on the experimental results, driver focus may vary among drivers with regards to his/her vehicle, the road, and surrounding vehicles.

In future work, further experiments need to be conducted to investigate the relationship between these weights and retrieval performance. The subjects were not categorized according to their driving skills in this study. However, if we compare the data from the questionnaires, which includes the subjects' driving experience and skills, with the weights of the subjects' foci while driving, some tendencies might become apparent. This needs to be investigated further. Other future work includes investigation of how driving data collected with cameras can be used to further improve driving scene retrieval performance, and to test the proposed method using a much larger database, including more kinds of driving scenes, such as scenes involving traffic accidents. The retrieval performance for more driving events, including driving straight ahead and traffic accidents, need to be evaluated objectively and subjectively. Retrieval speed should also be evaluated. Furthermore, it is necessary to compare the proposed method with some of the other stochastic models which have been proposed by other researchers.

Chapter 5

Conclusion

In this dissertation, I have described how data abstraction can be realized for the purposes of driving behavior evaluation and similarity measurement for driving behavior. Since raw data cannot be employed directly for data analysis, traditionally researchers have had to manually select data, which is a tedious and possibly subjective process. The two studies described in this dissertation proposed methods for extracting features from raw driving data and integrating them. These variables were then used to evaluate and measure driving behavior. The aggressiveness of driving behavior was evaluated in the first study, and similar driving behavior patterns were automatically retrieved in the second study, using the proposed methods.

To evaluate the aggressiveness of a driver's behavior, seven features were extracted as indicators of aggressive driving from drive recorder data and integrated. Principle component regression (PCR) was more effective for measuring aggressiveness than simple multiple linear regression (MLR), because the evaluated aggressiveness scores obtained using PCR were closer to the empirical scores given by driving safety assessment experts', which were the ground truth used in the experiment. In addition, increasing the number of feature variables did not always increase the accuracy.

In the second study, which measured the similarity of driving behavior in order to retrieve recorded data containing similar driving scenes, additional types of data recorded by multiple sensors were used. Employing six kinds of driving signals recorded by vehicle sensors, three features to measure the similarity of driving behavior were extracted. Since driving behavior can be better represented by combining features extracted from various sensor signals, similar driving scenes were retrieved more accurately. Furthermore, driver focus varied among drivers, depending on the driver's vehicle, the type of road, and the presence of surrounding vehicles. The proposed method in the first study could be applied to real-time evaluation of driver behavior, and would make it much easier to identify overly-aggressive drivers and provide them with feedback about their driving behavior. In addition, the method could be used for driver education, allowing driving instructors to retrieve examples of behaviors similar to those of driving school students, in order to provide additional counseling and instruction. The proposed method in the second study, could also be employed to train driver models with the retrieved data representing various driving behaviors, which could be used in the prediction of driver behavior.

These studies are only the first steps towards automating the data abstraction process, which is made possible through the collection of various types of driving data recorded with multiple sensors. Abstraction using data of interest to a specific driving behavior study is something we hope to address in future work. Although the features employed were selected empirically in these studies, the introduction of factorized information criteria (FIC) for automated feature selection, which has been successfully used in the field of data mining [80–82], could also prove to be of benefit to the field of driving data abstraction.

Additional types of sensors should also be considered in future studies in this field, since advanced driver assistance systems aim to not only improving traffic safety, but to also enhance comfort and driving pleasure. This will require the simultaneous collection of additional information using multiple sensors, to achieve a more holistic analysis of driving behavior. In such a system, sensor data fusion algorithms will be necessary to allow efficient combination of driving data recorded by the various different sensors. Although the technology for multi-sensor data fusion has been widely discussed in various fields [83–85], there are still many challenges to be overcome in order to effectively apply these technologies in intelligent transport systems [86].

Another big challenge is developing methods of predicting driving behavior by retrieving similar driving scenes, using the method proposed in the second study described in this dissertation. We believe that there are a number of frequent behavior patterns which occur when driving. For example, people may pass the same locations, such as the company where they work or their favorite shops, using the same routes day after day. The proposed driving behavior retrieval method could be employed to pick out similar patterns which occur along the same route, by integrating driving data with GPS data. As a result of modeling a sufficient variety of driving patterns, useful information could be provided to help the driver to perform various driving navigation tasks. Moreover, careful observation may reveal other general patterns, such as driver behavior during lane changes and when making turns. There are many potential benefits from such research, such as improving driving safety, reducing fuel usage and improving traffic planning.

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