Study on Robust Inattentive Driving Detection System with Driver Model and Dynamic Relational Network

September, 2013

Doctor of Engineering

MD Rizal Bin Othman

Toyohashi University of Technology

Abstract

Inattentive driving is an important safety problem. More than 25% of crashes are attributed to this aspect. Apart from the driver situation, the increased use of in-vehicle infotainment systems (IVIS) such as navigation systems, entertainment devices, real-time information systems and communications equipment in modern automobiles along with personal typical tasks such as eating and talking to passengers has further aggravated this problem. One promising solution for this problem can be realized by detection and estimation of driver inattention in real-time and then using the information together with advanced driver support systems (ADSS) to compensate the effects of the inattention or re-direct back the focus of the driver to the primary driving tasks. Therefore, the main purpose of this dissertation is to study a new robust method capable of detecting inattentive driving in real driving situation.

In the first part of this thesis (Chapter 3), a new method for the analysis of driver inattention using the driving operation signals is discussed. The proposed method involved with constructing a Nonlinear Autoregressive Exogenous (NARX) model as a driver-dependent modeling framework to capture the nominal behavior of the drivers. The models are then trained using the experimental data, validated, and used to predict the hypothetical nominal action of the drivers when they are actually driving with secondary tasks. The differences between the predicted nominal and actual distracted actions are analyzed to gain insights into how the secondary tasks affect the driver attention. Through assessment of the model residuals, the results demonstrate that the proposed method can differentiate and classify clearly between neutral and inattentive driving.

In the second part (Chapter 4), a novel method to detect inattentive driving automatically and systematically is proposed. Next, a comprehensive robust system for inattentive driving detection is developed. Here, the term ‘robust’ means that the system still could execute the detection process even though one of its inputs is absent (faulty sensor). In the studies of other researchers, the proposed models are

usually dependent on the input, where the model cannot predict the output correctly, if one of the inputs is not available and hence the overall system is suspended. To realize the robust detection system, inputs (sensors) diagnosis method is proposed using Dynamical Relational Network (DRN) to verify the state of the inputs (sensors). Based on the input available (healthy sensor), an appropriate model is chose to evaluate the driver inattention. Through this method the overall system reliability is enhanced and high-accuracy detection of inattentive driving is achieved even though one of the sensors in the system is malfunction. In conclusion, this study has proposed a robust system for inattentive driving detection. The results demonstrate that this system can classify driver inattention in real driving environment and can change its behavior based on available inputs.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

Driving is a common activity for many people, making driving safety an important issue in everyday life. Despite of safety improvements in road and vehicle design, the total number of road accidents still increases. The World Health Organization (WHO) reported that that every year around the world, more than 1.24 million people are died, while 50 million others are injured as a result of road accidents [1]-[4]. If this trends remains, report in [5] suggest that by 2030 road traffic deaths will become the fifth leading cause of death. Moreover, the costs of dealing with the consequences of these road traffic crashes are estimated at over USD100 billion a year [6]. The increasing number of road accidents and fatalities demonstrates that driving safety represents a persistent and important issue. Reducing crash involvement would benefit millions of people across the world.

Although most crashes are attributed to multiple causes, driver error represents a dominant one because drivers are responsible for operating vehicles and avoiding crashes [7]-[9]. Among all driver error, the studies found that the negligence of the driver is one of the biggest factors that cause accidents [10]-[11]. Miyaji et. al. [12], Hamada [13] and National Police Agency in Japan [14] reported in Japan that more than 25% of accidents are caused by drivers who lose concentration while driving a vehicle on the road. Furthermore, in 2006, National Highway Traffic Safety Administration (NHTSA) stated that 80% of crashes and 65% of near-crashes were caused by inattentive driving. The term inattention is usually used to refer to a driver state corresponding either to drowsiness or distraction. Drowsiness could be defined as the withdrawal of attention due to the physical condition of the driver [15]-[17]. While, distraction is defined as a shift in attention from the primary task (driving) to another task [18]-[21]. The problem becomes worse with increasing variety of additional infotainments system installed in vehicle that could cause the driver focus on driving distracted [22]-[24]. Therefore, the study of driver inattention is a key to finding a solution to solve in order to reduce the number of road accidents.

There are several approaches and methods have been employed by the research community for monitoring and detection of driver inattention. These approaches can be broadly divided into three groups: physiological measures [25]-[42], computer vision approaches [43]-[56] and driving performance measures [58]-[62]. The first approach utilizes physiological changes of driver for analysis of driver inattention. Physiological measures utilize biological signals such as the EOG, EEG, ECG, etc., which are collected through electrodes contacting the human body [9-15]. Then, signal processing methods were used to find the relationship between these signals and driver state. Heart rate is easily determined through Electrocardiogram (ECG) signal and it is used for detecting the driver's inattention. The heart rate increases by acceleration of the sympathetic nerve when a driver is imposed with cognitive tasks while driving [35]-[36]. When a driver is in a state of cognitive distraction, the effects of conversation, thinking, or other factors besides driving has a significant impact in the heart rate, thereby decreasing the RR Interval [37].

The EEG signal has various frequency bands which includes the delta band (0.5–4 Hz) corresponding to the sleep activity, the theta band (4–8 Hz) related with drowsiness, the alpha band (8–13 Hz) corresponding to relaxation and creativity, and the beta band (13–25 Hz) corresponding to activity and alertness [38]-[39]. Inattention is related to Beta band and so researchers have found features of beta band to find if the driver is inattentive. In one of the experiments, the power spectrum of the Beta band was found to be increasing as the driver got inattentive [40. C.T. Lin et al. [34] used Electroencephalography (EEG) power spectra to evaluate the brain dynamics in time-frequency domains, and suggested that theta band has some correlation with driver inattention.

Skin conductance increased when the driver was distracted through both visual and cognitive means [41]. Avinash et al. asked the drivers to answer a set of prerecorded questions through a cell phone to stimulate cognitive distraction and then they were asked to send short message service (SMS) during driving. Considerable increase in skin temperature (ST) in the supraorbital region was observed on all participants during both cognitive as well as visual distractions. This ST change is an outcome of altered blood supply to the supraorbital, which is an indirect measurement of mental activities [42]. Although these methods can provide more accurate results, they are impractical in real driving situations because they always require attachment of devices to the driver.

The second approach, computer vision is more practical as it is non-intrusive to the driver; hence many active studies have been conducted in this field and a number of comprehensive methods have been accomplished so far. Eye movement metrics, such as eye blinks, pupil dilation and gaze angle have been used to find distraction [43]-[44]. The eye blink, the rapid eye closing and opening of the eyelid, is believed to be an indicator of both visual and cognitive distraction. It was found out that the eye blink duration or blink frequency increased substantially during the driver distraction [44]-[46]. The pupil is the part of the iris that allows light to enter the retina. Besides light, the pupil dilates when mental or cognitive effort is given. It was observed that the pupil was dilated and the diameter of average pupil size increased by 15 % when the driver was distracted [44]. Suzuki et. al. [56] in his study, detect eyelids using a neural network from driver’s face image, which captured by a camera placed in car, and proposed a method to estimate driver alertness based on the movement of eyelids.

Gaze angle is used as a metric to find if the concentration of the driver was on driving or if he/she was taking more time in interacting with IVIS or if he/she was viewing side mirrors properly. It was noted that, when the driver was distracted, glancing at instruments and mirrors decreased significantly [43]. The gaze position and head position was measured in the experiment conducted by Engstorm et al. and it was found that the Standard Deviation (SD) of gaze angle decreased substantially when the driver was distracted visually and cognitively [41]. In [51] the authors proposed the use of Active Appearance Models to model the driver's face and extract seven characteristic points. Facial analysis was carried using these characteristic points in order to detect driver drowsiness. Dinges et al. [33] proposed one of the most widely accepted metrics known as Percentage Eyelid Closure (PRECLOS) for the detection and evaluation of drowsiness through computer vision approach.

On the third approach, researchers are interested to study the effects of inattention driver on driving performance. Similar to computer vision approach, this approach also have the advantage of being non-intrusive to the driver compared with the first approach. Ishikawa et al. [58] proposed a method to detect inattentive driving with secondary tasks using driving behavior signals modeled with a Bayesian network. They showed that it is effective to consider driving situations when detecting distracted driving involving secondary tasks. Here the primary task is normal driving operation and secondary tasks such as talking on a cell phone, reading road sign and searching song on the radio are imposed on the driver. However, the proposed method only can achieve up to 76% of detection rate and need for the improvement. Kuroyanagi et al. [59], furthermore, analyzed hazardous situations in actual driving environment based on level of scene danger and driver response. They confirmed that driver response decrease while driving with secondary tasks. This shows that secondary task can be a good tool to create distraction to driver during actual driving task. In addition to low detection rate, the proposed method uses following distance (distance between car) as one of the inputs to the model. Following distance is vulnerable to the external environment such as heavy rain, snow, etc., which will cause the system capability to be reduced. Pilutti et al. [57] studied the relation between drowsiness and driving performance. However, only data from simulated environment were used in the study because of the risks of involving drowsy drivers in real situation. Moreover, most of the studies described above only focused on detecting inattention caused by drowsiness and fatigue. Inattention caused by the distraction (cognitive and visual) has been less explored and discussed.

Accurately identifying driver inattention using real driving data is a critical challenge in developing driver support systems in order to minimize road accidents. However, to our knowledge, the drawbacks of previous studies can be summarized as follow:

1. Most of the previous studies only use data from simulated environment because of the risks of involving inattentive drivers in real situation.
2. Methods using physiological measures are not practical to be implemented in real driving situations because they always require attachment of devices to the driver.
3. Most of the studies that used computer vision approach, only focused on detecting inattention caused by drowsiness and fatigue. Inattention caused by the cognitive distraction has been less explored and discussed.
4. Some researchers are study the detection of inattention driver using driving performance measures since this approach have the advantage of being non-intrusive to the driver. However, the detection rate of the proposed method is low and need for the improvement. Furthermore, some of the proposed method uses external signal (e.g. following distance) as one of the inputs to the model, which vulnerable to the external environment such as heavy rain, snow, etc., that will result the system capability to be reduced.

1.2 Objectives and Contributions

In this study, in order to improve above problem, a new robust system that can perform driver inattention caused by cognitive distraction has been developed. As shown in Figure 1.1, the flowchart of the detection system proposed in this research is presented.

The overall objective of this thesis is to study and develop detection method for inattentive driving caused by cognitive. To achieve this overall goal, the following objectives will be accomplished.

1. To study and investigate the relation between drivers cognitive distraction and

driving performance signal.

2. To proposed a new method to detect inattentive driving cause by cognitive distraction.

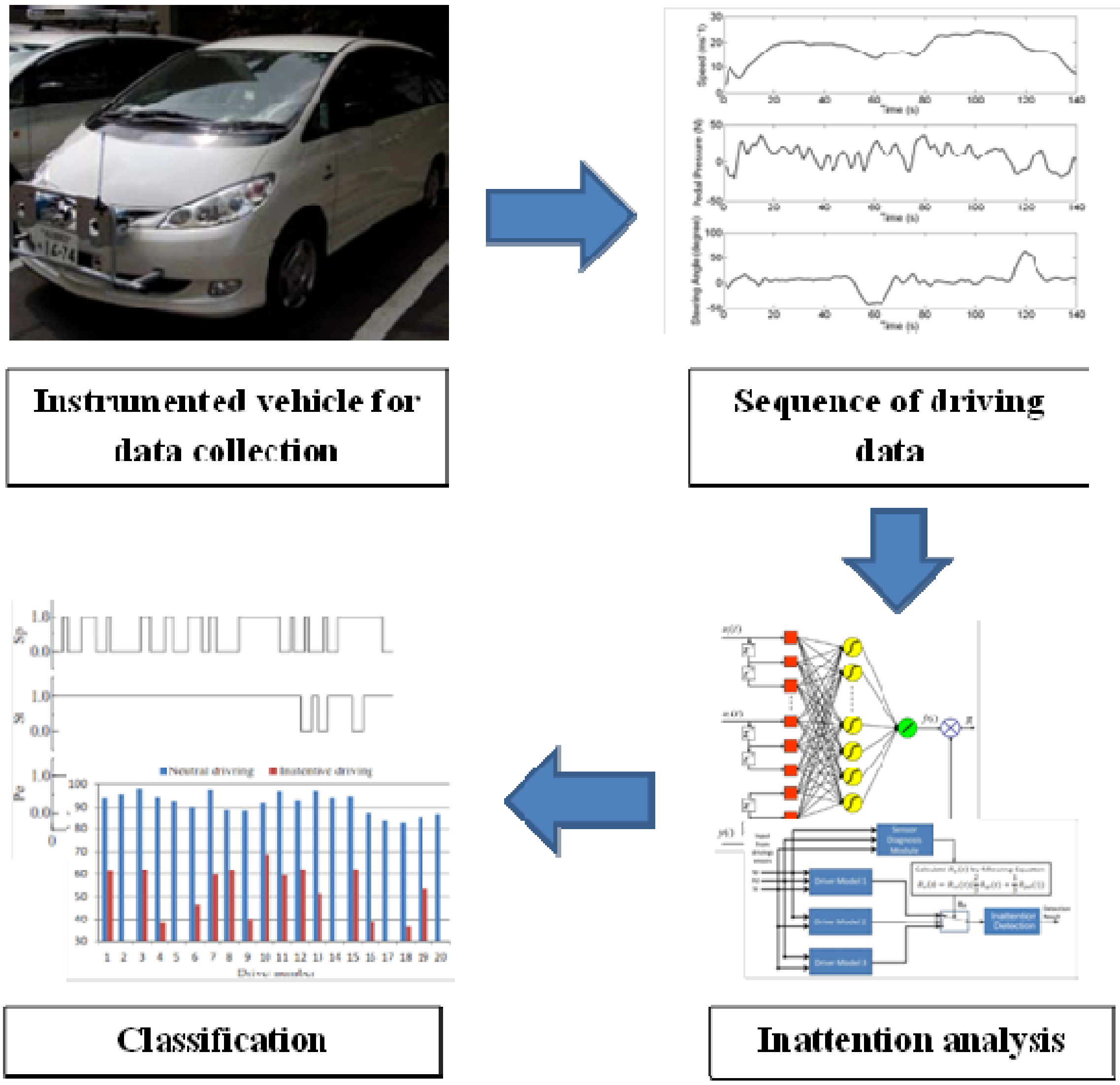


Figure 1.1: The flowchart of the new inattentive driving detection system

The contributions of this thesis include:

1. Experiment setup and data collection in real driving environment. The data has been use widely as a standard data in multiple research fields related to safety driving,

2. Investigating how cognitive distraction affected driver performance,

3. Develop and establish driver model to detect inattentive driving,
4. Proposed and develop driving sensor diagnosis method to increase system reliability and detection rate.

1.3 Thesis Organization

The thesis organization is summarized and shown in Figure 1.2.

In Chapter 1, the general background, research problem, previous work in the research field and its limitation are introduced and discussed.

In Chapter 2, a detail explanation regarding experiment that has been conducted, type and conditions of data collection in real environment is discussed. Two categories of driving data were collected; (1) data from ordinary driving and (2) data from driving with secondary tasks. Data collected from driving with secondary task was consider as inattentive driving data since secondary task has been accepted as important source of driver distraction.

Chapter 3 proposes the new model-based analysis and classification of inattentive driving caused by cognitive distraction.

In Chapter 4, a new in-vehicle sensor diagnosis module to increase overall system reliability is proposed and discussed. The sensor diagnosis module using the Dynamic Relational Network is developed to analyse and identify faulty sensors through its measurement data. Next, the integration between inattention detection system and sensor diagnosis module is discussed. The overall driver inattention system was tested with actual data from a car driving on highway. The results obtained indicate the effectiveness of our proposed method.

Finally, Chapter 5 summarizes the contributions of this work and highlights some suggested directions for future research.

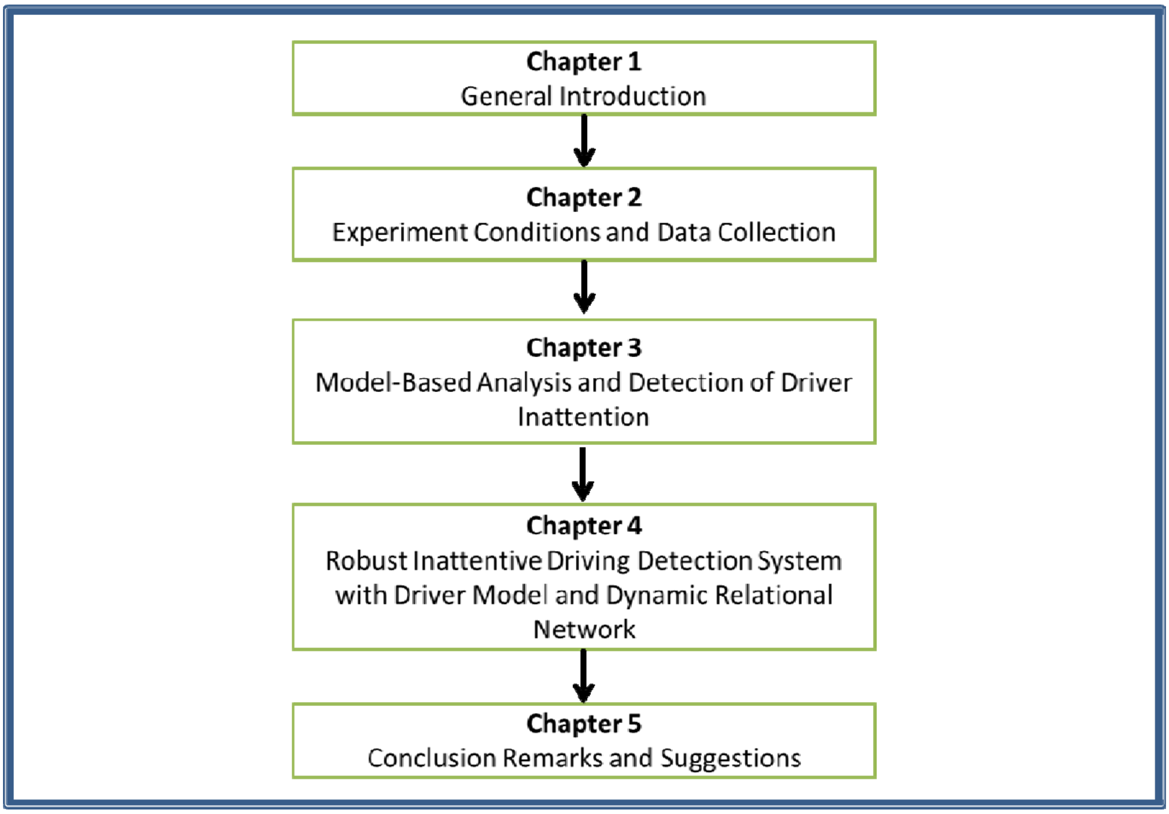


Figure 1.2: Outline of the thesis

Chapter 2

Description of Experiment and Data Collection

2.1 Introduction

Inattentive driving is an important safety concern, as discussed in the previous chapter. Generally, inattentive driving can be caused by two types of distraction; visual and cognitive distraction. Visual distraction can be described as “eye-off-road” and cognitive distraction as “mind-off-road”. Both of them can undermine drivers’ performance [63]-[71]. Visual distraction is straightforward, occurring when drivers look away from the roadway (e.g., to adjust a radio), which can be reasonably measured by the length and frequency of glances away from the road [64]. Unlike visual distraction, cognitive distraction occurs when drivers think about something not directly related to the current vehicle control task (e.g., conversing on a hands-free cell phone or route planning). However, in this paper we are interested to detect inattentive driving caused by driver cognitive distraction. There are five types of measures for driver inattention detection [72]-[77]: (1) subjective report measures (e.g., survey form); (2) driver biological measures (e.g., EEG, ECG); (3) driver physical measures (e.g., PERCLOS, gaze direction); (4) driving performance measures (e.g., steering wheel angle, gas pedal, speed); (5) hybrid measures.

Since cognitive distraction needs to be done in real time and non-intrusively, the subjective report measures and driver biological measures are not suitable for a real-life context.

Therefore, this chapter will discuss the experiments that have been conducted, the conditions for collecting driving data so that it is valid to be used for inattentive driving detection and other matters regards to data collection.

2.2 Review of Source of Inattentive Driving

Some drivers are capable of adapting their driving behaviour to meet the increased demands of engaging in non-driving tasks while driving. However, under certain conditions these adaptive behaviours can breakdown, resulting in a significant degradation in driving performance. The potential for a non-driving task to distract the driver is determined by the complex interaction of a number of factors including task complexity, current driving demands, driver experience and skill and the willingness of the driver to engage in the task. A non-driving task that distracts drivers and degrades driving in one situation may not do so in another situation and, similarly, non-driving tasks may differentially affect drivers from different driving populations. Recently, driver distraction research has focused on identifying those conditions under which engaging in secondary tasks while driving is most likely to distract drivers to the extent that their driving performance and safety is compromised. Generally, research has found that as the difficulty of the secondary and/or driving tasks increase, the potential for the task to degrade driving performance also increases. The distraction caused by interacting with in-vehicle devices while driving has been shown to significantly impair a driver’s ability to maintain speed, throttle control and lateral position on the road. It can also impair drivers’ visual search patterns, reaction times, decision making processes and can increase the risk of being involved in a collision. Moreover, research findings suggest that drivers are not always aware of the detrimental effects on their driving

Figure 2.1 The instrumented vehicle used in the experiment

performance of engaging in secondary tasks and often underestimate the risks involved in performing particular tasks, particularly in relation to their own crash risk relative to their peers. A number of task and driver characteristics that can influence the potential for non-driving tasks to distract drivers have been identified in the literature. The National Highway Traffic Safety Administration stated that the secondary tasks which affected driving performance are concluded (not limit to) as follows:

1. Using a cell phone or smartphone
2. Adjusting a radio, CD player, or MP3 player
3. Reading, including maps
4. Using a navigation system
5. Talking to passengers
6. Eating and drinking
7. Grooming
8. Watching a video
9. Texting

2.3 Experimental Description

The driving data utilized in this study are from in-car signal corpus hosted at the Center for Integrated Acoustic Information Research (CIAIR), Nagoya University, Japan [59]. The experiments were conducted during 2007 and 2008 in collaboration with Professor Kazuya Takeda's Laboratory, Nagoya University, Japan. Multidimensional and multimodal consists of speech, image, control (driving) and physiological data has been recorded under both driving and idling conditions. The collection and recording of the data was carried out with the data collection vehicle (DCV), an instrumented vehicle specially built to achieve the synchronous capturing of multichannel audio, video, and vehicle related data. Figure 2.1 shows the DCV and placements of the recording devices. The collected data also is a part of the Large Scale Real World Database which aims to promote the research that used real driving data.

2.4 Types and Condition of data

Driving data collected during the experiment can be grouped into two; data collected under ordinary driving and under driving with secondary tasks. Secondary task is an important source of driver distraction [78] that could cause inattentive driving, which may impair the driver even more than intoxication at the legal limit. A wide range of secondary tasks have been investigated for their impact on driving [72]-[77]. All these and many other investigations have confirmed that secondary

tasks have a detrimental effect on driving performance. Therefore, there are four different secondary tasks used in this study: 1) a navigation dialog task, 2) an alphanumeric reading task, 3) a signboard-reading task and 4) a music retrieval task. Table 2.1 shows all twelve experiments, types of road and their conditions during the data collection. Figure 2.2 shows the course map used in this study, where mark (1) denotes the start location, marks (2) to (7) and (12) to (13) denote city roads and marks (8) to (11) denote highway roads. A total of 114 subjects with different background participated in the experiments. The driving experiment was to drive the DCV along the course road as shown in Figure 2.2. The course road was divided into 13 experiments with different condition of driving and type of road. During the driving events, researcher recorded all driving performance data as ordinary driving data (ODD) for regular driving and inattentive driving data (IDD) for driving with secondary task. An example of ODD data that was measured in experiment 8 is shown in Figure 2.3, where (a) shows the outside image of the car, and facial image of a driver and (b) shows the operation signals. In Figure 2.3(b), the top figure shows the car speed, the bottom figure shows the steering angle and the middle figure shows the pedal pressure. The sampling rate of the operation signals is 100[Hz]. Note that the pedal pressure signal shown in Figure 2.3(b) is a synthetic signal, which was made to be the sum of the gas pedal pressure (made to be positive) and the brake pressure (made to be negative). Hereafter, we call such pedal pressure the synthetic pedal pressure.

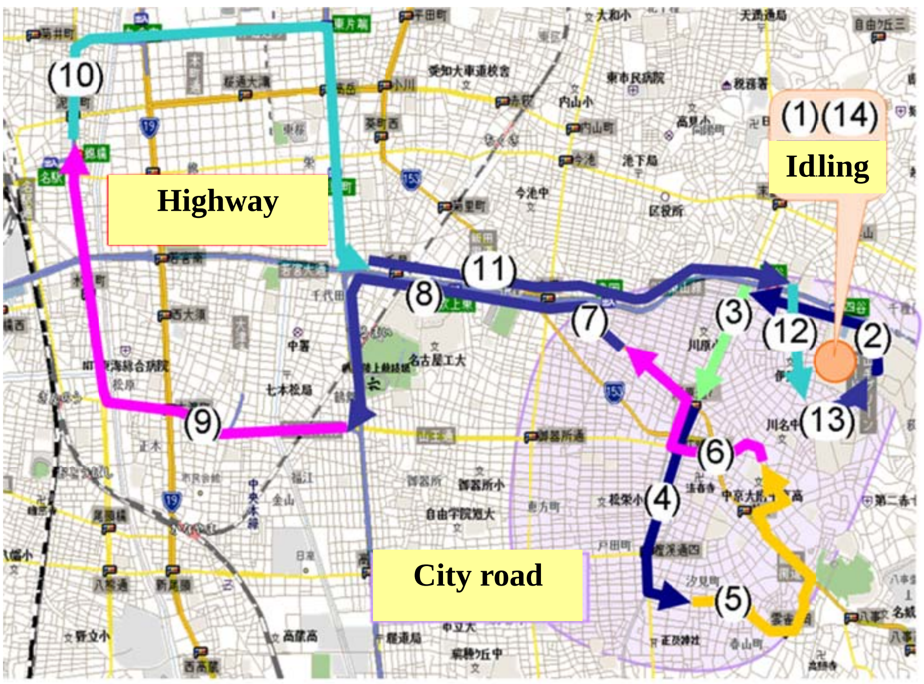
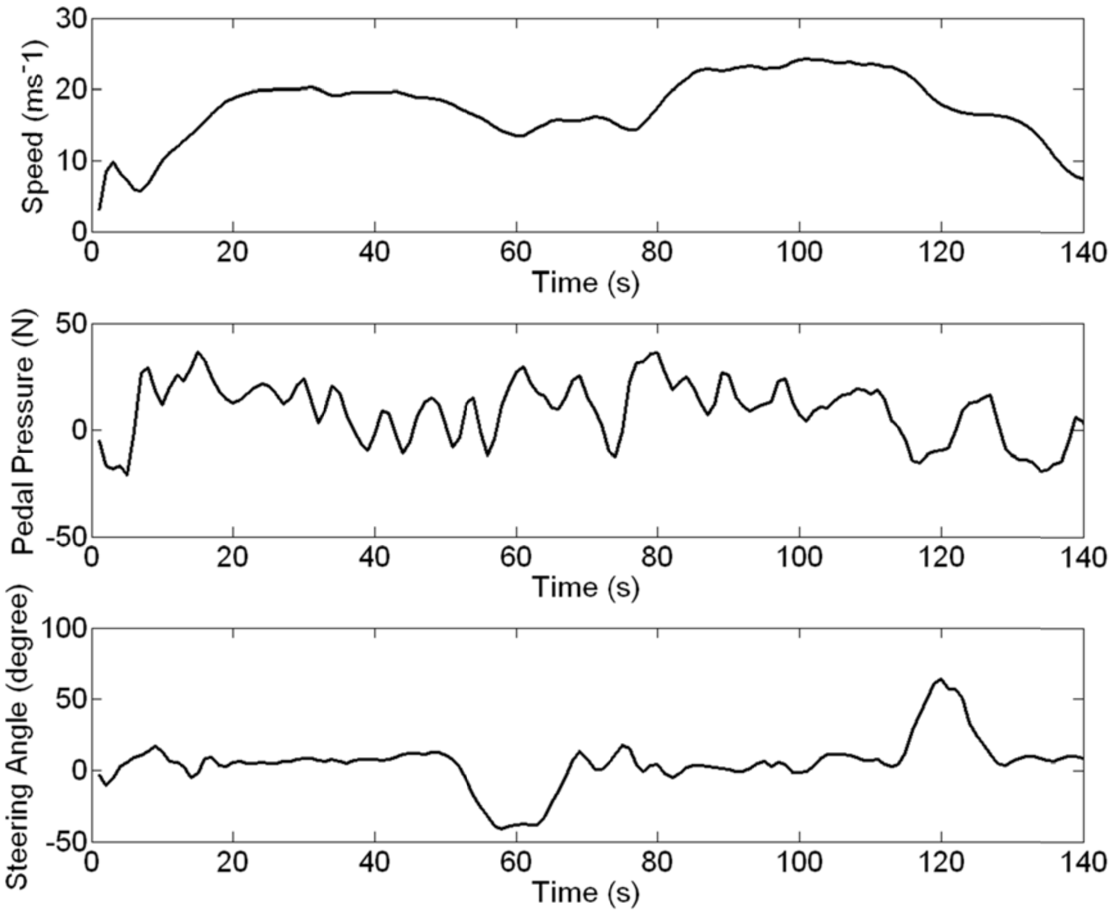


FIGURE 2.2. The course map used in this study

(a) Audio and video data



(b) Driver operation signal and vehicle data

FIGURE 2.3. Example of driving data collected during the experiment.

TABLE 2.1. Description of experiments and driving conditions

Experiment	**Type of road**	**Task**	**Description**
1	-	Idling	
2	City	Ordinary driving	Driving without extra task
3	City	Signboard reading	Reading aloud information on signboards
4	City	Ordinary driving	Driving without extra task
5	City	Navigator	Following navigator instructions in an unfamiliar place
6	City	Alphanumeric verbalization	Repeating four alphanumeric letters
7	City	Ordinary driving	Driving without extra task
8	Highway	Ordinary driving	Driving without extra task
9	Highway	Alphanumeric verbalization	Repeating four alphanumeric letters
10	Highway	Song retrieving	Song retrieving by spoken dialog interface
11	Highway	Ordinary driving	Driving without extra task
12	City	Song retrieving	Song retrieving by spoken dialog interface
13	City	Ordinary driving	Driving without extra task
14	-	Idling	

2.5 Measures Selection

In general, it is well accepted that driving performance will degrade in inattentive driving. This is because the recognition of information needed from visual and cognitive attention to correctly and/or safely accomplish the driving task is delayed due to non-driving related activity. Since inattentive driving caused by cognitive distraction needs to be done in real time and non-intrusively, driving performance measures (e.g., steering wheel angle, gas pedal, speed) were used in this study. A question arises. What type of driving performance data that the most affected in inattentive driving? In order to investigate the overall effect of the secondary tasks on the driver performance, we calculate the average and standard deviation for the operation signals that include (experiments 9 and 10) or do not include (experiments 8 and 11 shown in Table 1) secondary tasks for all drivers. Figure 2.4, 2.5 and 2.6 show the calculation results, where Figure 2.4 denotes the average values of the vehicle speed, Figure 2.5 denotes the average values of the synthetic pedal pressure and the Figure 2.6 denotes the standard deviation of the steering angle. Based on these values, it is obvious that in the case of the operation with a secondary task the average values of vehicle speed and the synthetic pedal pressure are smaller than those in case without a secondary task. Compared to this, the standard deviation of steering angles has a bigger difference between the cases with and without secondary tasks. This means that in the case of a secondary task, the steering angle has bigger turbulence than when there is no secondary task and driving performance significantly degraded. That is, the steering angle is more sensitive to the secondary task. Based on these values, it is obvious that the inattention driving have significant effects to some driving performance variables. Among these variables, steering angle is the performance variable that most affected by inattention driving.

2.6 Conclusions

1. The experiment in this study was design for collecting driver inattention data caused by cognitive distraction.
2. Secondary tasks are use as the source of distraction in the experiment. Four different types of secondary task were used in this study.
3. the experiments were performed using real data collected vehicle (DCV) in collaboration with Professor Kazuya Takeda's Laboratory and Center for

Integrated Acoustic Information Research (CIAIR), Nagoya University.

4. Premenelary analysis show that steering angle performance variable has significant effect due to inattentive driving.

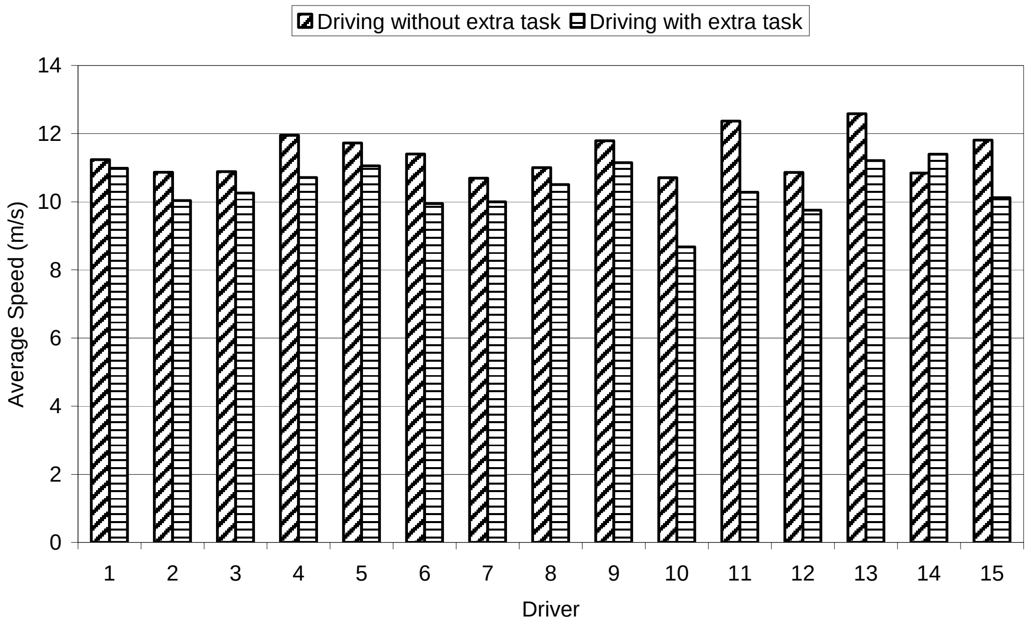


Figure 2.4 The effect of neutral and inattention driving average speed

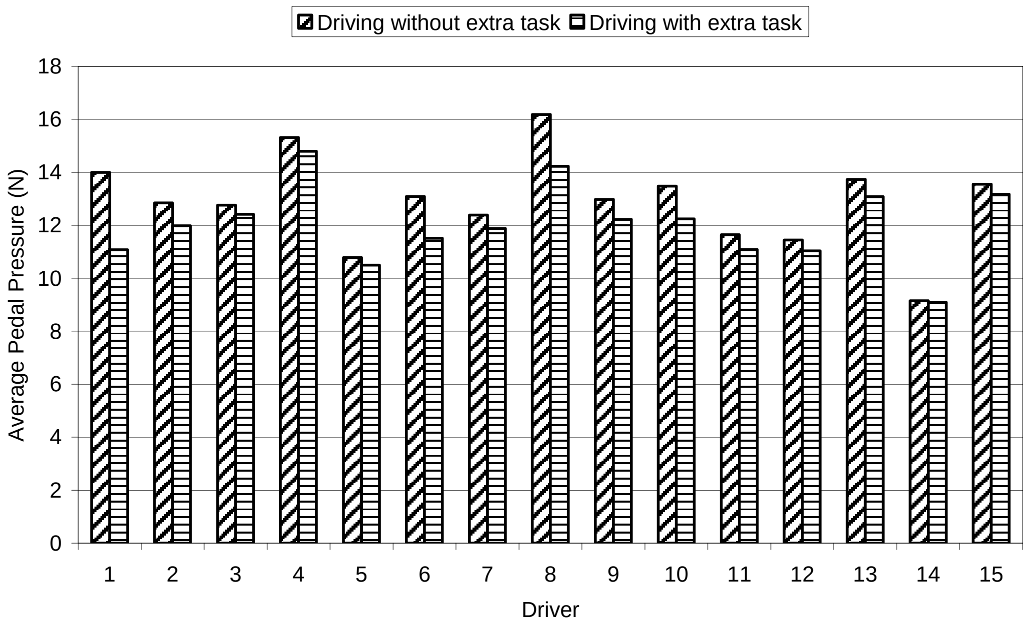


Figure 2.5 The effect of neutral and inattention driving average pedal pressure

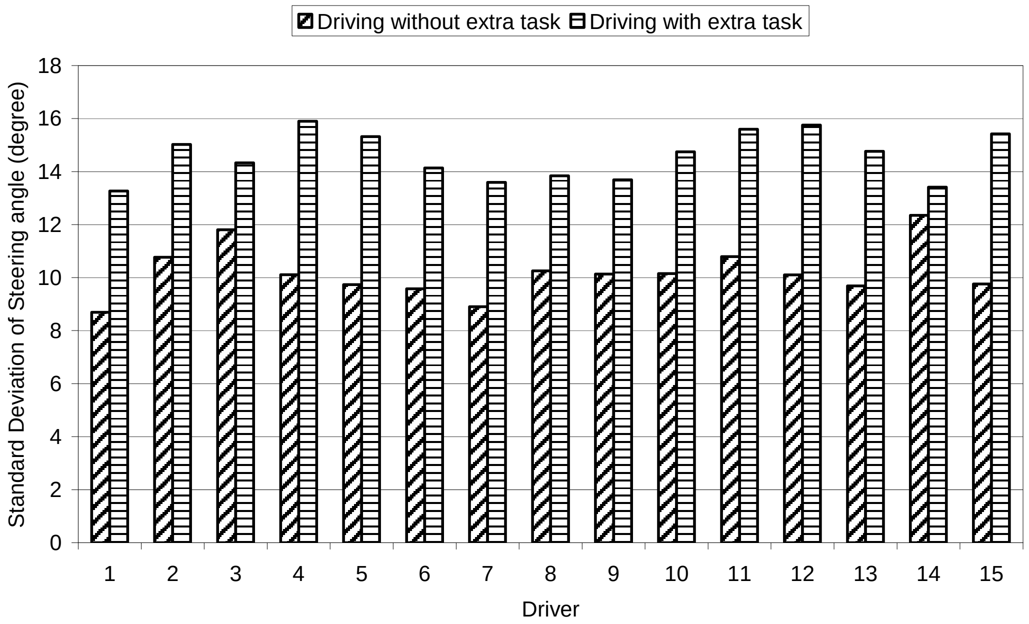


Figure 2.6 The effect of neutral and inattention driving on steering angle

Chapter 3

Model-Based Analysis and Detection of Driver Inattention

3.1 Introduction

Chapter 2 described about experimental setup and the condition of driving data collection. The data collected during the experiment can be grouped into two; ordinary driving data and inattentive driving data. Inattentive driving data was obtained by imposes secondary task to the driver. In this section, the data was used to develop and verify the proposed model-based analysis and detection of driver inattention.

Many researchers have explored and developed driver model for difference purposes. Newcomb and McLean [79]-[80] provide examples of fairly detailed modelling of the various components of the driver-vehicle system during longitudinal braking. Rompe's work [81] in addition to Newcomb and McLean also provides a useful source of measurements of representative driver model during hard braking. The work of Fancher and Bareket [82] is primarily concerned with the headway control behaviour of typical drivers and their interaction with Automatic Cruise Control (ACC) systems during highway driving. Peng's recent work [83] using a modified version of the Gipp's model [84] is likewise advancing the modelling effort in the headway control area and appears to accurately represent both macroscopic as well as microscopic traffic flow behaviour of human drivers. In summary, all of these driver models were developed in order to analyse either vehicle stability or longitudinal and lateral control. Only a few researchers develop driver model for the purpose of inattention driver analysis. For example, Ishikawa et al. [58] use driving behavior signals modeled with a Bayesian network to detect inattentive driving with secondary tasks. However, the proposed method at best can achieve a correct detection rate of only 76% and so there is need for improvement. Kuroyanagi et al. [59], furthermore, analyzed hazardous situations in actual driving environment based on level of scene danger and driver response. They confirmed that driver response decrease while driving with secondary tasks. This shows that secondary task can be a good tool to create distraction to driver during actual driving task. In addition to low detection rate, the proposed method uses following distance (distance between car) as one of the inputs to the model. Following distance is vulnerable to the external environment such as heavy rain, snow, etc., which will cause the system capability to be reduced. Therefore, in this study we proposed a new model-based approach to analyze inattentive driving. The proposed model utilize driving data such as steering angle, pedal pressure and vehicle speed that less dependent to external environment.

3.2 A New Model-Based Analysis and Detection of Driver Inattention

Generally, the driving performance shows a driver's ordinary behavior and it can be shown by the operation signals, such as the gas pedal, brake, steering angle signals and car speed. It is well accepted that driving performance will degrade when driving with some secondary tasks. In previous chapter, we proved that steering angle can be significantly affected by inattentive driving. This is because the recognition of information needed from visual and cognitive attention to correctly and/or safely accomplish the driving task is delayed due to non-driving related activity. Therefore, by analyzing the differences between ordinary driving and driving with some secondary tasks in terms of driving operation signal (such as gas pedal, brake, steering angle and car speed), it is possible to detect driver inattention. Through this concept, we proposed a model based approach to detect the inattentive driving caused by cognitive distraction. To be more specific, a baseline model is developed to characterize the normal driving behaviour of a driver when driving without secondary tasks. The model is then used in a scenario of driving with a secondary task to predict the hypothetical actions of the driver, had there been no secondary tasks. The difference between the predicted normal behaviour and the actual distracted can provide useful information of inattentive driving.

In most systems, linear models such as partial least squares (PLS), Auto Regressive with Exogenous inputs (ARX) and Auto Regressive Moving Average with Exogenous inputs (ARMAX) only perform well over a small region of operations. For these reasons, a lot of attention has been directed at identifying nonlinear models such as neural networks, Volterra, Hammerstein, Wiener and nonlinear autoregressive exogenous input (NARX) model. Among of these models, the NARX model provides a powerful representation for time series analysis, modeling and prediction due to its strength in accommodating the dynamic, complex and nonlinear nature of real time series applications [85]. Therefore, in this work, NARX is used to model ordinary driving operation signal.

3.2.1 Structure of Driver Model

In this study, the model output in terms of the driver behavior is assumed to be a function of the past and present input, and the past output. Mathematically, this relation can be represented as a multivariable nonlinear autoregressive exogenous input (NARX) model of the following form:

$$\hat{y}(t) = f[u_1(t), u_1(t-1), \ldots, u_1(t-k), u_n(t), u_n(t-1), \ldots, u_n(t-k), y(t-1), \ldots, y(t-k)] \tag{3.1}$$

where $u(t)$ and $y(t)$ are the model inputs, $\hat{y}(t)$ is the estimated model output, n is the number of inputs and k is the model time delay. In this study, there are three input signals (n=3), where $u_1(t)$ denotes the vehicle speed, $u_2(t)$ denotes the synthesis pedal pressure and $y(t)$ denotes the steering angle, respectively. The general function $f(\cdot)$ can be estimated using several identification methods. However, we chose to use a neural network-based method due to its capability of incremental learning without changing the model structure. Therefore, the function $f(\cdot)$ is approximated by a multilayer perceptron (MLP) model with a nonlinear transfer function in the middle layer; hence, the model is called a NARX network. Based on our previous study [61], a tansig and linear function were used in the middle and output layers, respectively, in order to obtain a model with high generalization. Figure 4.1 shows the structure of the NARX network used in this study.

The NARX network performs its calculations such that the output of the *j*-th neuron in the middle layer is expressed as equation (3.2):

$$h_j = g_j\left[\sum_{i=1}^{n}\left(w_{ji}u_i + b_j\right)\right], \quad i = 1, \ldots, n, \;\; j = 1, \ldots, n_j \tag{3.2}$$

where $u_i(t)$ is the *i*-th network input, w_{ji} is the connection weight from the *i*-th neuron in the input layer to the *j*-th neuron in the middle layer, b_j is the weight from the bias to the *j*-th neuron, $g_j(\cdot)$ is a nonlinear activation function in the middle layer, which in this study is the tansig function. Then, the network output is calculated by the following relation as shown in equation (3.3):

$$\hat{y}_o = g_o\left[\sum_{j=1}^{n_j}\left(w_{oj}h_j + b_o\right)\right], \quad j = 1,\ldots,n_j,\ o = 1 \tag{3.3}$$

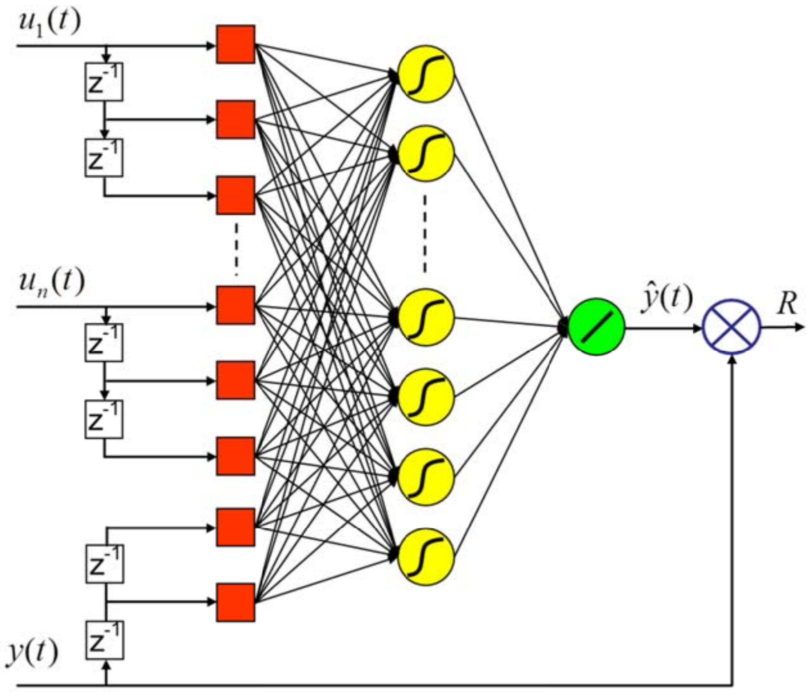


Figure 3.1 The structure of the NARX network

where w_{oj} is the weight connecting the j-th neuron in the middle layer to the output neuron in the output layer, b_o is the bias weight for the output neuron, $g_o(\cdot)$ is a transformation function in the output layer and is a linear function in this application.

The popular back-propagation algorithm for training the NARX network is a gradient descent-based algorithm and is subject to slow convergence. To improve convergence, a superior second-order Newton method based on the Levenberg-Marquardt algorithm [86]-[87], is used in this study to train the overall models. In addition, the Levenberg-Marquardt algorithm is widely used for optimization and it outperforms simple gradient descent and other conjugate gradient methods on a wide variety of problems. In this study, the aim of the Levenberg-Marquardt algorithm is to compute the weight vector $\vec{w}$ so that the error $E(\vec{w})$ in equation (3.4) is minimize.

$$E(\vec{w}) = \sum_{l=1}^{k} e_l^2(\vec{w}) = \| f(\vec{w}) \|^2 \tag{3.4}$$

where $e_l(\vec{w}) = y_l - \hat{y}_l(\vec{w})$, y_l is the target value and $\hat{y}_l(\vec{w})$ is the output (predicated) value of output neuron l and $\vec{w} = [w_{11}, w_{1,2}, \cdots, w_{ji}, w_{o1}, w_{o2}, \cdots w_{onj}]^T$. The $E(\vec{w})$ is an objective error function made up of k individual error terms $e_l^2(\vec{w})$. By means of the Levenberg-Marquardt algorithm, a new weight vector $\vec{w}_{m+1}$ can be obtained from the previous weight vector $\vec{w}_m$ as follows:

$$\vec{w}_{m+1} = \vec{w}_m + \delta\vec{w}_m \tag{3.5a}$$

where $\delta\vec{w}_m$ is defined as:

$$\delta\vec{w}_m = \frac{-(J_m^T f(\vec{w}_m))}{(J_m^T J_m + \lambda I)} \tag{3.5b}$$

In equation (3.5b), J_m is the Jacobian of $f(\cdot)$ evaluated at $\vec{w}_m$, λ is the Marquardt parameter and I is the identity matrix [61]. In summary, the learning algorithm used to train driver model in the form of NARX network can be summarized as follows:

(i) Calculate $E(\vec{w}_m)$ by using equation (4.4),

(ii) Begin with a small value of λ e.g. $\lambda = 0.01$,

(iii) Solve (4.5b) for $\delta\vec{w}_m$ and compute $E(\vec{w}_{m+1})$,

(iv) If $E(w_{m+1}) <$ target error, then stop the training process,

(v) If $E(\vec{w}_{m+1}) >$ target error and $E(\vec{w}_{m+1}) \geq E(\vec{w}_m)$, then increase λ by a factor of 10 and repeat step (iii),

(vi) If $E(\vec{w}_{m+1}) >$ target error and $E(\vec{w}_{m+1}) \leq E(\vec{w}_m)$, then decrease λ by a factor of 10, update $\vec{w}_m : \vec{w}_m \leftarrow \vec{w}_{m+1}$ and repeat step (iii).

3.3 Model Fitting and Validation

The operation signals of neutral driving from experiment 8 without the secondary task were used for model fitting for each driver. Model fitting was carried out by the learning process described in Section 3.2. The model was then validated using the operation signals from experiment 11 without the secondary task. The driving duration was not exactly the same for all drivers, and therefore the amount of data available varied for each driver. The NARX network was used to predict the output from three inputs. In this study, the steering angle is used as the model output, while the vehicle speed, synthetic pedal pressure and actual steering angle were used as inputs since the steering angle is more sensitive to the secondary task than the vehicle speed or synthetic pedal pressure. We think it is a novel idea to evaluating the difference (model residual) between the actual steering single (which is the input signal) and the predicated steering angle (which is the output signal) in order to detect the inattentive driving. This is because in the case of inattentive driving, the driver operation was different from normal (neutral) driving and has some turbulence, hence the model cannot predict correctly and the predicted error becomes bigger.

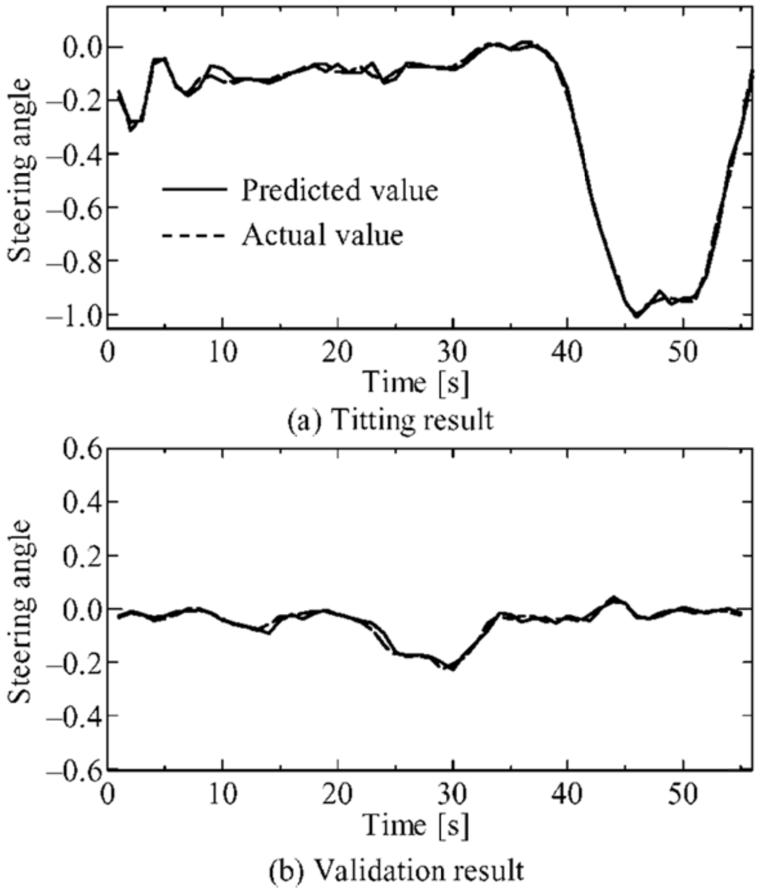


FIGURE 3.2 Example of the actual signals and predicted values of driver action, where (a) shows the fitting result and (b) the validation result.

Figure 3.2 show examples of predicted values of driver action for driver 1 during fitting and validation processes, where (a) shows the model output obtained by fitting process, (b) shows the model output obtained by the validation process. In order to compare the predicted values with actual operation signal, the actual steering angle that is one of the inputs also is shown in Figure 3.2. By comparing the actual steering angle with predication results, one can observe that the model prediction closely follows the actual driver action in the condition of fitting and validation, which proved that the model produces suitable output from new inputs with a high confidence rate.

3.4 Inattention Analysis using Driver Model

As discussed in the previous section, the driver model can predict the output very well for new inputs operation signals for neutral driving. In other words, this model can capture driver's operation characteristic patterns, the correlation between the inputs and output, and important properties from ordinary driver behavior in performing driving tasks. Therefore, when a driver drives normally, the model residual, which is the difference between the predicted values and the actual steering signal, should have a small standard deviation and be in the form of white noise. However, when this model is used data from driving with a secondary task, the standard deviation increases showing that the model can differentiate between ordinary and inattentive driving. In this study, operation signals from experiment 9 were used as the inattentive driving data to test the model. In experiment 9, each driver is instructed to loudly repeat four randomized alphanumeric letters that are given through the driver's earphone. This process continues until end of the experiment. Through this process, the cognitive attention of the driver while driving is distracted due to the secondary task.

Figure 3.3 shows examples of the predicated value and actual value in the case of inattentive driving, where (a) shows the result obtained from the driver 1 and (b) shows the result obtained from driver 14. As can be seen, the residual value between the predicated value and the actual steering signal is bigger. The same result can also be obtained from all 15 drivers. These results proved that the proposed method was capable of detecting inattentive driving caused by cognitive distraction.

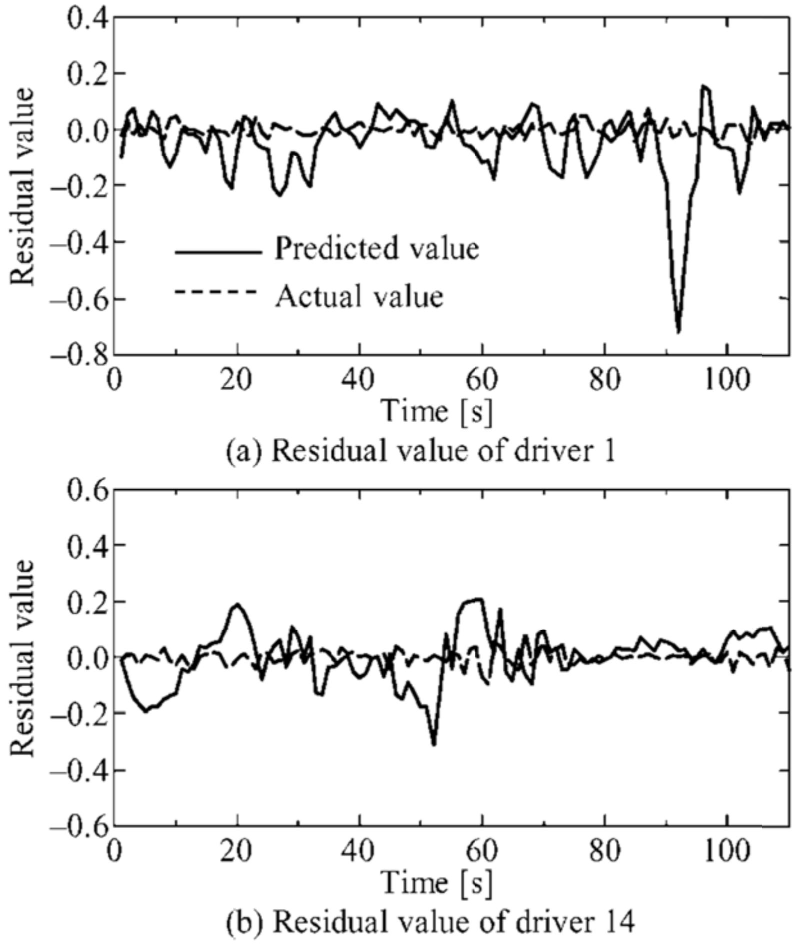


FIGURE 3.3 Examples of the predicated value and actual values in the case of the inattentive driving, where (a) shows the result obtained from the driver 1 and (b) shows the result obtained from driver 14.

3.5 Evaluation of Analysis results

The performance of the model was analyzed by studying the model residuals, i.e. the differences between the actual operation signal and model-predicted driver actions. Furthermore, the root mean square (*RMS*) value of the model residual was calculated using equation (3.6) in order to confirm the model performance.

$$RMS = \sqrt{\frac{1}{s}\sum_{r=1}^{s}(e_r)^2} \qquad (3.6)$$

where $e_r = (\hat{y}_r - y_r)$, $\hat{y}_r$ is the model-predicted value at time r, y_r is the actual steering angle at time r and s is the number of data.

Figure 3.4 shows the *RMS* value of the model residual in the cases of neutral driving (experiment 8 for fitting and experiment 11 for validation process) and inattention driving (experiment 9) for all 15 drivers. As can be seen in Figure 3.4, in the case of neutral driving, the *RMS* values for fitting and validation are very small for all 15 drivers, which also indicate the effectiveness of the model. That is, the model can almost predict the output value exactly even though the difference data were used for these processes. Comparing to this, in the case of inattention driving, the *RMS* values are almost more than two times larger than in the case of neutral driving. This also indicates the effectiveness of the model for inattentive driver detection.

In addition, we also calculated the percentage of confidence score for the model residuals obtained for the cases with and without the secondary task for all drivers to observe the effectiveness of the model for inattentive driving detection. The percentage of confidence score was calculated based on equation (3.7).

$$C = 100e^{-R_{rms}} \; [\%] \qquad (3.7)$$

where C is the percentage of confidence score, $R_{rms} = aRMS \times RMS$, RMS is calculated using equation (6) and $a = 30$ is a constant value.

Equation (3.7) explained that the percentage of confidence score depends on the residual's value. If the residual's value is small which shows that the driver is driving neutrally, the value of confidence score, *C* will be high. In contrast, if the residual's value is big which shows that the driver is inattentively driving, the value of confidence score, *C* will be low. Figure 3.6 shows the percentage of confidence score obtained from neutral driving (validation process) and inattentive driving data. As can be seen, the percentage of confidence score is very high and is more than 90[%] for the neutral operation residual whereas for inattentive operation the score drops below 70[%] excepting the tenth driver. This result indicates the effectiveness of the model for inattentive driving detection and also shows that the percentage of confidence score can be used to interpret how much the driver is affected by distraction from the given task. Furthermore, the percentage of confidence score differs for each driver. We think this is due to the fact that the influence of the secondary task for inattentive driving is differs based on different driving experiences, and the driver's behavior.

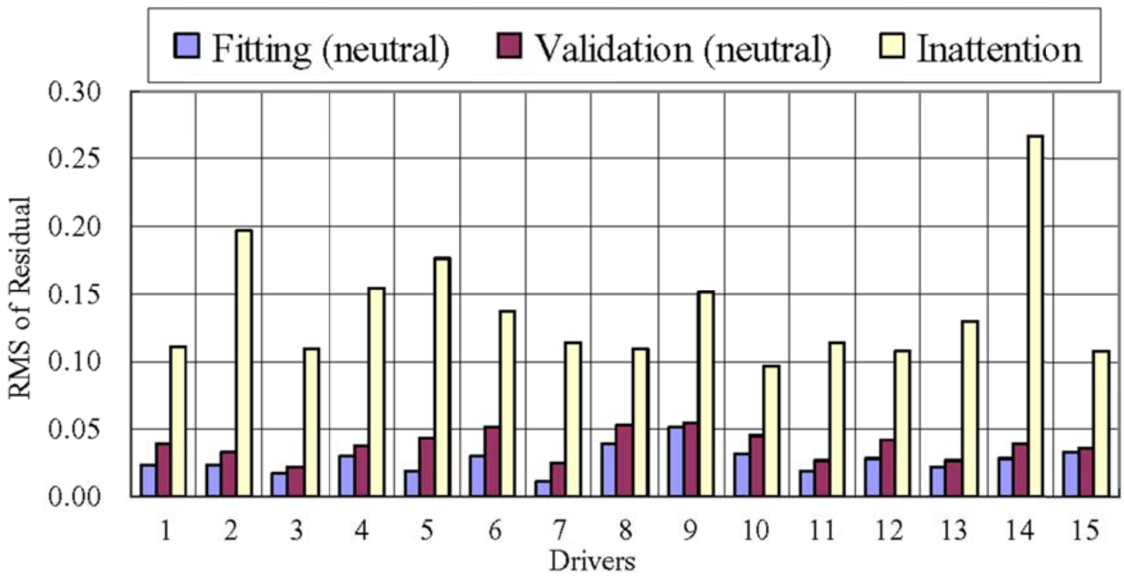


FIGURE 3.4 *RMS* values of the neutral driving (fitting and validation process) and the inattention driving for all drivers

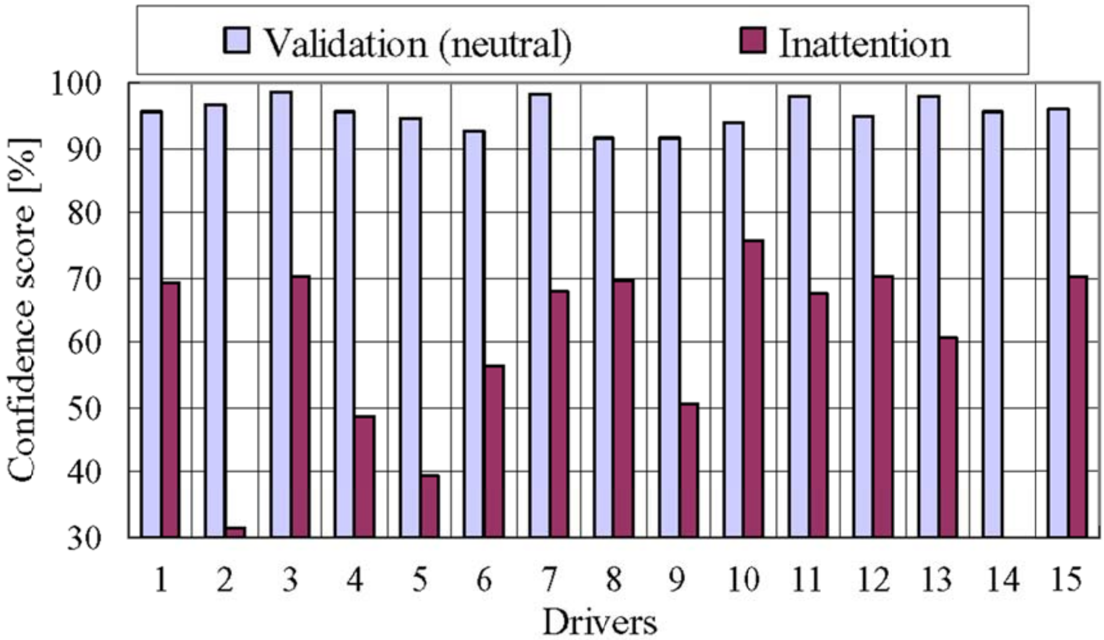


FIGURE 3.6 The percentage of confidence score from validation and inattention driving data for the all drivers

3.6 Conclusion

This section proposed a new method to identify driver inattention in driving tasks caused by cognitive distraction. The method involved constructing a neural network-based NARX model for each driver using neutral driver operation signals (i.e. without a secondary task). The results obtained show that in the case of neutral driving, the percentage of confidence score for the model residuals is very high and is more than 90[%] whereas in the case of inattentive driving, the score drops below 70[%]. It has been shown that the model is capable of demonstrating the effects of inattention on individual drivers through its residual value. Therefore, by using our method the inattention in driving caused by cognition distraction can be detected, although it is difficult by using traditional method, which focused on detecting inattention caused by fatigue and visual distractions.

Chapter 4

Robust Inattentive Driving Detection System with Driver Model and Dynamic Relational Network

4.1 Introduction

In Chapter 3, we proposed a new method to identify driver inattention due to cognitive distraction using a model-based technique. The method uses in-vehicle driving data collected by various sensors to predict output. Driver inattention is detected by analyzing the difference between the predicted and actual output, i.e., the residual of the model. The results demonstrated that the proposed method could differentiate and clearly distinguish between neutral and inattentive driving, however the detection rate dropped when one of the input sensors failed. Therefore, sensor failure diagnosis is needed in order to obtain an optimum detection rate and to avoid false alarms of the detection results.

Several studies have been done to detect and identify sensor failure. Li et al. [89] proposed a linear model to model the process and thus the resultant residual is expressed in the form of a linear function. Simani et al [90] used a linear state-space model to create a bank of observers and assumed only one sensor fault in the measurement process. Based on the residual generated, this method can identify a single faulty sensor. However, many real processes including driver behavior are naturally nonlinear. Thus a linear model usually cannot hold the signal distribution well and the proposed methods can only give good predictions with some constraints.

Nevertheless, a dynamic relational network (DRN) has been proposed as an effective technique for the abnormality diagnosis of the system with a large number of sensors [92]-[96]. It can express a diagnosis object as an inequality limitation between variables in the observable condition when the diagnosis object is not expressed as a closed equation model. In addition, the DRN can perform the diagnosis that reflects the object when it cannot judge the object from a given sensor level exactly. Yamada et al. [97] proposed a consistency diagnostic method of front vehicle recognition with the DRN using the data obtained by a laser radar and image sensor, and confirmed its effectiveness.

In this chapter a new robust system that can perform driver inattention detection will be discussed. Here, the term `robust' means that the system can still execute the detection process even when one of its inputs is absent (a faulty sensor).
To progress towards this objective, this chapter first constructs an in-vehicle sensor diagnosis module by DRN using the data from sensors, such as the vehicle speed and pedal operation. Then, a driver inattention detection system by combining the sensor diagnosis module and the driver model is introduced for the purpose of monitoring the state of the driver in the car and the detection of inattentive driving. The effectiveness of the proposed system is also evaluated in an actual car driving on an expressway by using each operation data in the state that imposes a secondary task that causes inattentive driving and the state that does not impose a secondary task.

4.2 A New Inattentive Driving Detection System by Using Dynamic Relational Network (DRN)

As is shown in Chapter 3, when data from inattentive driving is used, the driver model cannot predict output well, hence it produces a big residual. However, if one of the sensors is damaged or not functioning properly, the proposed model also cannot provide good results, and sometimes it even gives the wrong detection result. This is because the model assumes that the driver is not driving in a normal condition due to wrong data collected by the faulty sensors. This situation can be avoided if we can exclude the faulty sensor's signal and only use the signal from the normal sensors as inputs into the detection system. Therefore, sensor failure diagnosis is needed in order to obtain an optimum detection rate and to avoid false alarm detection. In this section, a method of driving sensor diagnosis using the DRN will be discussed. Then a new inattentive driving detection system will be introduced.

4.2.1 Principe and Dynamics of the Dynamic Relational Network (DRN)

In this section, the principle of Dynamic Relational Network (DRN) is discussed. DRN is a system consisting of different types of nodes that are linked together to form a network. One important feature of DRN is that each node can evaluate other node or can be evaluated by other node independently and propagates its current state, dynamically [99]-[101]. This feature makes the DRN can be used as a diagnostic system to detect faulty nodes.

Suppose that a measurement system is consist of multiple heterogeneous nodes, S_i where $i = 1,2,3,..,m$, tied together with a link to form a network. The diagnosis of the node whether it is normal or faulty is carried out by determines the

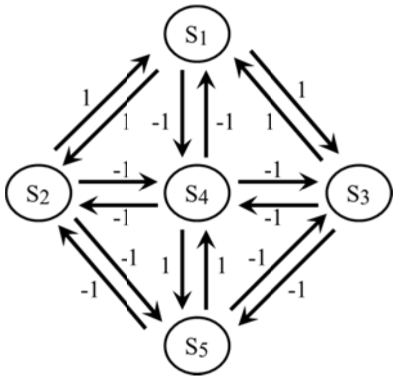


FIGURE 4.1. Dynamic Relational Network with 5 nodes and the value of T_{ij}

relationship of mutual trust between the nodes. The relationship between node S_i and S_j, that linked together is judged by using measured value $x_i(t)$ and $x_j(t)$ of node S_i and S_j. If node S_i and S_j have maximum matchability, a test value, T_{ij} is assigned to 1 ($T_{ij} = 1$). On the contrary, if nodes S_i and S_j, have no matchability, then $T_{ij} = -1$ is assigned. This process is performed between all linked nodes in the system. Figure 4.1 shows an example of the DRN with 5 nodes and the value of T_{ij}, where number 1 of the arc indicate that $T_{ij} = 1$ and -1 indicates that $T_{ij} = -1$.

The state of the node (normal or abnormal) cannot be determined by simply obtaining a test value for each unit. However, which node is abnormal can be detected by including dynamics in this network [101], for example as expressed below:

$$\frac{dr_j(t)}{dt} = \sum_i T_{i,j}^{+}(t) R_j(t) \tag{4.1}$$

$$T_{i,j}^{+} = T_{j,i}(t) + T_{i,j}(t) - 1 \tag{4.2}$$

$$R_j(t) = \frac{1}{1+e^{-r_j(t)}}, \tag{4.3}$$

$$r_j(t) \in (\infty, +\infty),\ \ R_j(t) \in (0,1)$$

Where $R_j(t)$ represents the credibility or reliability of node, S_j at time t, $r_j(t)$ its intermediate variable and T_{ij} the test value obtained by S_i testing S_j. Initially, the reliability value $R(t)$ of all nodes at $t = 0$ is set to 1. Equations (4.1) and (4.2) are renewal equations for converging the network. Equation (4.3) is a sigmoid function and this network is known to converge [101]. If $r_j(t)$ is large, the $R_j(t)$ is converge to 1. Otherwise, if $r_j(t)$ is small, the $R_j(t)$ is converge to 0. A node that ultimately has low reliability when the network has converged is determined to be abnormal.

4.2.2 A New DRN Structure for In-vehicle Sensor Diagnosis

For the purpose of monitoring the condition of in-vehicle sensors that are used to collect driving data, the diagnosis algorithm is constructed based on the DRN's principle, where nodes in the DRN are replaced with an in-vehicle sensor. At first, the sensor network is constructed by connecting all the sensors to each other with virtual arcs. In this study, the relationship between each sensor is analysed as follows and the DRN network is built.

Drivers always regulate speed by stepping on the accelerator pedal and the brake pedal and repeating this operation. Here the operation quantity of the accelerator pedal and the brake pedal, which are measured by different sensors, is treated as one pedal operation quantity because they are related to the adjustment of speed. And the quantity of the accelerator pedal is defined as a positive value and the quantity of the brake pedal is defined as a negative value. Corresponding to this, the two sensors measuring the quantities of the conventional accelerator pedal and brake pedal are treated as one virtual sensor. Based on the quantity of pedal operation and relation with the vehicle speed, the quantity of the pedal operation and vehicle speed are firstly tied with an arc.

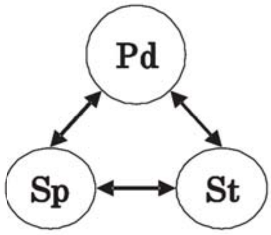


Figure 4.2. The DRN for excursively driving

Generally, a car often travels at more than 70[km/h] on an expressway. Even if the car is going straight, steering wheel operation is necessary for fine adjustment. In addition, if it is not going straight even if it is said to be going straight, the operation that quite a few near cornering may be performed. In this case, it is thought that there is an action to decrease the vehicle speed, and to operate the steering wheel. Therefore, the steering angle and vehicle speed are tied by an arc.

As shown above, there is an operation action to decrease vehicle speed while driving and operate the steering wheel. It is necessary to regulate the quantity of pedal operation to decrease vehicle speed. In other words it is thought that there is an action to operate the steering wheel by adjusting the quantity of pedal operation. Therefore, the quantity of pedal operation and the steering angle is tied by an arc.

Based on the above-mentioned argument, the three virtual sensors measuring the quantity of pedal operation, vehicle speed and steering angle are represented by three nodes of the DRN and the network is built. Figure 4.2 shows the built network for in-vehicle sensor diagnosis. The P_d in the figure shows the quantity of the pedal operation sensor, S_p the vehicle speed sensor, and S_t the steering angle sensor. Descriptions like these are used, hereafter.

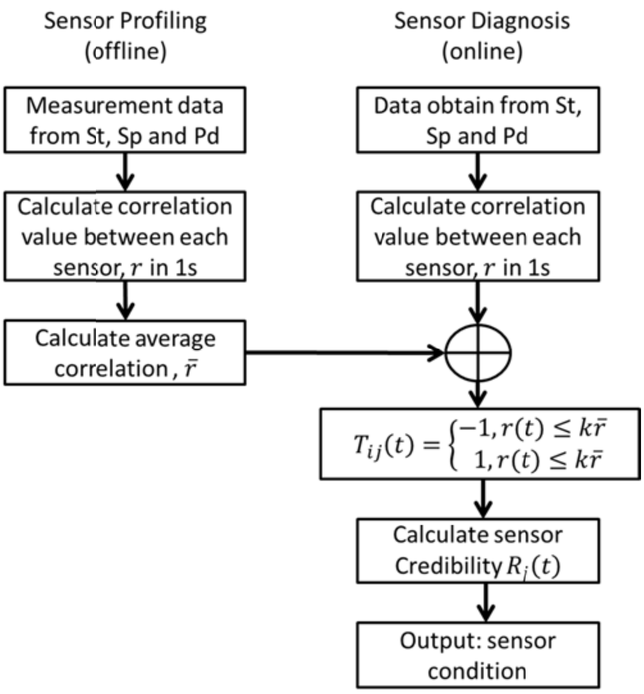


Figure 4.3 Sensor Diagnosis Module using DRN

4.2.3 Sensor Diagnosis Module with the In-Vehicle Sensor DRN

This section will discuss a new sensor diagnosis module to identify sensor failure used in collecting driving data. Figure 5 shows the proposed sensor diagnosis module. As is shown in Figure 4.3, the sensor diagnosis module can be divided into two parts: offline sensor profiling and online sensor diagnosis. Offline sensor profiling part aims to extract the relationship between sensors that were tied together in a network. The relationship is obtained by calculating the proper parameter of normal data collected by the sensor. This step was performed offline and the parameter obtained will be used as a baseline or threshold value in the online sensor diagnosis part.

In this study, we use correlation coefficient to represent the relationship between sensors tied in the network. Let Si and Sj are two sensors connected together via an arc and $x_i(t)$ and $x_j(t)$, are measurement data from normal sensor S_i and S_j, respectively. The correlation coefficient was calculated on every tenth (10) sample data xi and xj using the following equation:

$$\rho_{ij}(\tau) = \frac{1}{m-1}\frac{\sum_1^m (x_i(t)-\bar{x}_i)(x_j(t)-\bar{x}_j)}{\sigma_{x_i}\sigma_{x_j}} \tag{4.4}$$

Where $\rho_{ij}(\tau)$ is the correlation coefficient, m is the number of sample in a window, σ_{x_i} and σ_{x_j} are standard deviation of data $x_i(t)$ and $x_j(t)$, respectively. Then, the baseline correlation coefficient $\bar{\rho}_{ij}$ is obtained by averaging of all correlation coefficient over M number of windows using the following equation:

$$\bar{\rho}_{i,j} = \frac{\sum_1^M \rho_{ij}(\tau)}{M} \tag{4.5}$$

In the sensor diagnosis part, the current correlation coefficient, $\rho_{ij}(\tau)$ that is calculated using online measurement data $x_i(t)$ and $x_j(t)$, of sensors S_i and S_j is compared with the baseline correlation coefficient $\bar{\rho}_{ij}$. When $\bar{\rho}_{ij}$deviates from the calculated $\rho_{ij}(\tau)$ by a predetermine amount (called a threshold), the test node, $T_{ij}(\tau)$ is decided as -1. In summary, the test node, $T_{ij}(\tau)$ is decided based on the following rule:

$$T_{ij}(\tau) = \begin{cases} -1, & \rho_{ij}(\tau) < k\bar{\rho}_{ij} \\ 1, & \rho_{ij}(\tau) \geq k\bar{\rho}_{ij} \end{cases} \tag{4.6}$$

Where k is a constant value, $\bar{\rho}_{ij}$ is baseline correlation coefficient, $\rho_{ij}(\tau)$ is

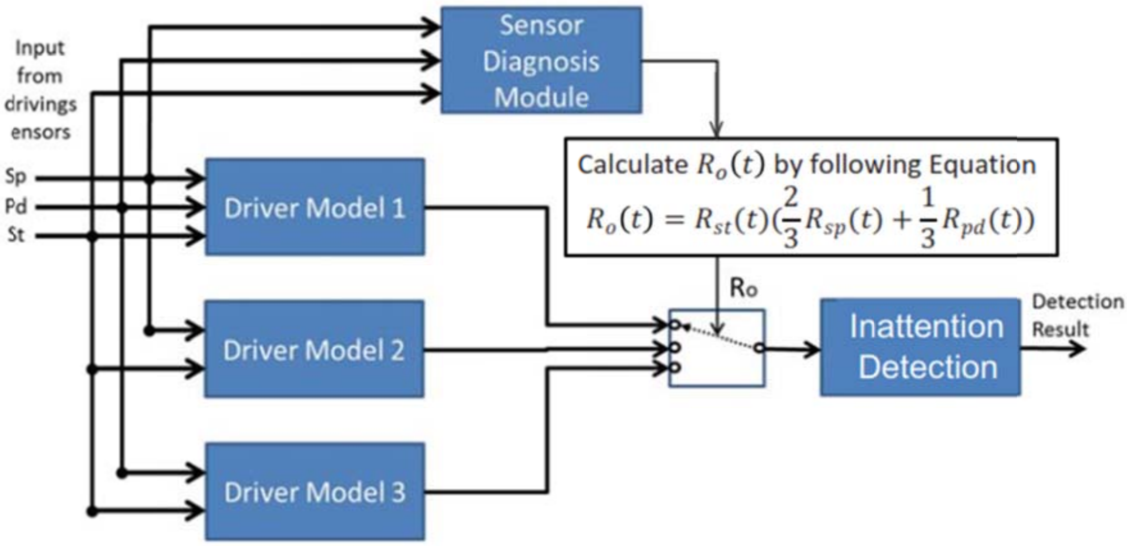


Figure 4.4: Inattentive driving detection system with DRN-based sensor diagnosis and driver model

current correlation coefficient and $T_{ij}(\tau)$ is a test unit of the relationship of sensor S_j to sensor S_i. After the test unit, $T_{ij}(\tau)$ of the correlation between sensorS_i and S_j have been decided, the credibility $R_j(\tau)$ of sensor S_i is calculated using Expression (4.1), (4.2) and (4.3).

4.2.4 Driver Inattention Detection System by using Driver Model and Sensor Diagnosis Module

In order to overcome the influence of faulty sensors on the detection rate of inattentive driving, a novel inattentive driving detection system based on the sensor diagnosis module and driver model is proposed. The idea is to eliminate the signal from a failed sensor before inattention detection is done by the driver models. By doing this, the signal from a faulty sensor will not affect the output of the driver models.

Table 4.1: The interpretation of $R_o(t)$ and sensor state

R_o	Sensor State
1	All sensors are OK
$2/3$	Problem with pedal sensor
$1/3$	Problem with speed sensor
0	Problem with steering sensor

Figure 4.4 shows the overall concept of the inattentive driving detection system. As is shown in Figure 4.4, the system can be divided into three parts: the sensor diagnosis module shown in Figure 4.3 and Section 4.2.3, the driver model shown in Figure 3.1 and Section 3.2 and the inattention detection part. The sensor diagnosis module analyses and identifies a faulty sensor (if any) through its measurement data. This module will produce total sensor credibility $R_o(t)$ that indicates the status of the input sensor of the system. $R_o(t)$ is obtained by using the following expression:

$$R_o(t) = R_{St}(t)(\frac{2}{3}R_{Sp}(t) + \frac{1}{3}R_{Pd}(t)) \tag{4.7}$$

Where R_{St} is the credibility of steering sensor, R_{Pd} is the credibility of pedal sensor and R_{Sp} is the credibility of steering speed sensor. These credibility values indicate whether the respective sensor is working properly or not. The R_{St}, R_{Pd}, and R_{Sp} values were calculated individually using the sensor diagnosis module. Table 4.1 shows the interpretation of $R_o(t)$ and the sensor state. As can be seen in Table 4.1, Equation 4.7 is easily understandable since it gives a direct interpretation about the sensor's state. Therefore, $R_o(t)$ can be used as a selector to choose a suitable driver model for inattentive driving detection.

In the driver model part, three driver models were developed in the system. Driver model 1 is a normal model that has three input sensors shown in Section 3.2, while driver models 2 and 3 have only two input sensors. Based on Equation (4.7) and Table 4.1, if all input sensors are normal, the output of the sensor diagnosis module is $R_o(t)$, thus the output of driver model 1 is chosen. If a pedal sensor is diagnosed as having failed, in other words $R_o(t) = 2/3$, the output of driver model 2 will be used to detect inattentive driving. The same concept is applied when $R_o(t) = 1/3$, which means that the speed sensor is faulty, and then the output of driver model 3 will be used for the detection. However, if the total sensor credibility $R_o(t) = 0$, where the steering sensor is the problem, then inattentive driving detection cannot be performed because the output of each model cannot be computed.

In addition, in the inattention detection part, the percentage of confidence score is calculated by using the driver model residuals, which are obtained for the cases with and without a secondary task for all drivers, for inattentive driving detection.
The percentage of confidence score is calculated based on the following equation:

$$C = 100e^{R_{RMS}} \text{ [\%]} \tag{4.8}$$

where C is the percentage of confidence score, R_{RMS}= $aRMS \times RMS$, where RMS is calculated using Equation (3.6) and $a = 40$ is a constant value. Equation (4.8) shows that the percentage of confidence score depends on the residual's value. If the residual's value is small which shows that the driver is driving neutrally, the value of the confidence score, C will be high. In contrast, if the residual's value is big which shows that the driver is inattentively driving, the value of the confidence score, C will be low.

4.3 Confirmation Experiments and Results Discussion

4.3.1 Driving Data

The driving data utilized in this study were collected in collaboration with Professor Kazuya Takeda's Laboratory, Nagoya University, Japan. A real vehicle equipped with various sensors and cameras was used for synchronous recording of data, which consists of video, speech, driving control and physiological signals.
The aim of these experiments were to record multimodal driving data on different types of roads, such as city roads and expressways, under ordinary driving and with four tasks, in order to collect neutral and inattentive driving data.

The four different secondary tasks are: 1) a navigation dialog task, 2) a repeating alphanumeric task, 3) a signboard-reading task and 4) a music retrieval task. Figure 2.2 in Chapter 2, shows the course map used in this study, where mark (1) denotes the start location, marks (2) to (7) and (12) to (13) denote city roads and marks (8) to (11) denote highway roads. Table 2.1 in Chapter 2 shows all twelve portions of the experiments that correspond to numbers (2) to (13) shown in Figure 2.2, the types of roads and their conditions during data collection.

On the city road, changes often occur outside of the car, such as pedestrians crossing and road traffic signals changing. Besides these, every car performs a variety of driving actions such as coming to a complete stop, turning left or right, and going slowly. In this study, in order to pay attention to the state of the driver, we want to remove elements such as the environment out of the car and the driving condition of the car if it is possible. Therefore, the driving data of the Highway are used. The operation signals of experiments 8, 11 (without secondary task) and 9 (with a secondary task of alphanumeric repeating), 10 (with a secondary task of music retrieval) from 20 licensed drivers were selected as examples, in order to investigate the influence of the secondary task on the driver's performance and to confirm the difference between inattentive driving and neutral driving. For the same reason, only the data when driving straight is treated.

An example of driving data that was measured from the operation signals in experiment 8 is shown in Figure 2.3 in Chapter 2, where the top figure shows the car speed, the bottom figure shows the steering angle and the middle figure shows the pedal pressure. The sampling rate of the operation signals is 100[Hz]. Note that the pedal pressure signal shown in the top figure is a synthetic signal, which was made to be the sum of the gas pedal pressure (made to be positive) and the brake pressure (made to be negative). In addition, in a part of the Highway, a secondary task such as alphanumeric repeating and music retrieval was assigned to the drivers, and driving without a task was defined as neutral driving and driving with a secondary task was defined as inattentive driving.

4.3.2 Faulty Sensor Detection using the Sensor Diagnosis Module

There are many types of sensor failure, however here we consider a constant fault as an example because this type of failure occurs during the experiments and data collection. A constant fault happens when a sensor reports a constant value for a large number of successive samples. The reported constant value is either zero, very high, very low compared to the normal sensor reading and uncorrelated to the underlying physical phenomena. Examples of driving data with this type of sensor failure are shown in Figure 4.7, which is neutral driving data of driver 18 with a speed sensor

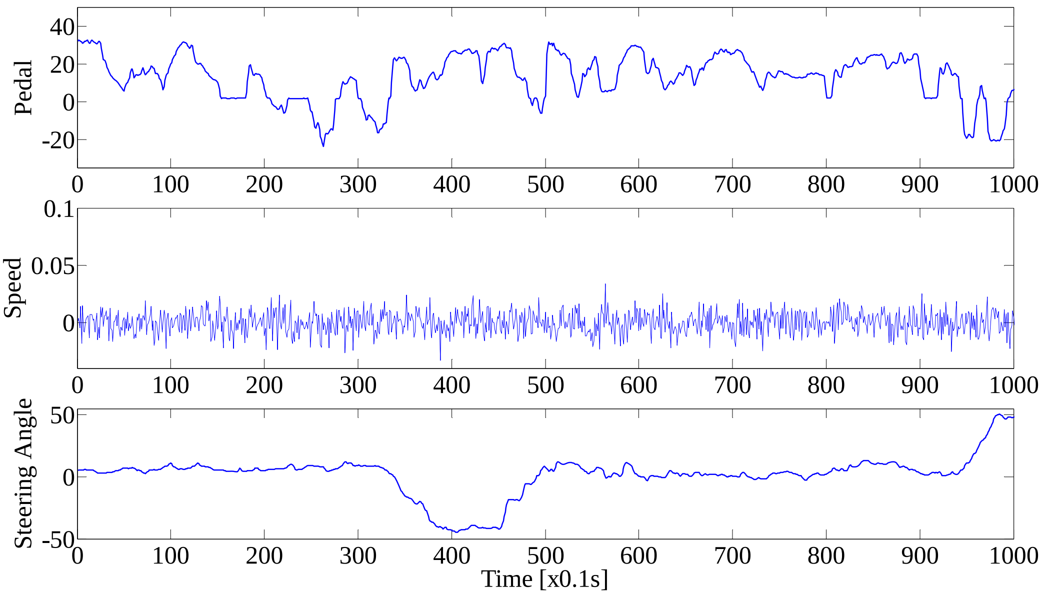


Figure 4.5: Example of neutral driving data of driver 18 with speed sensor failure in experiment 8

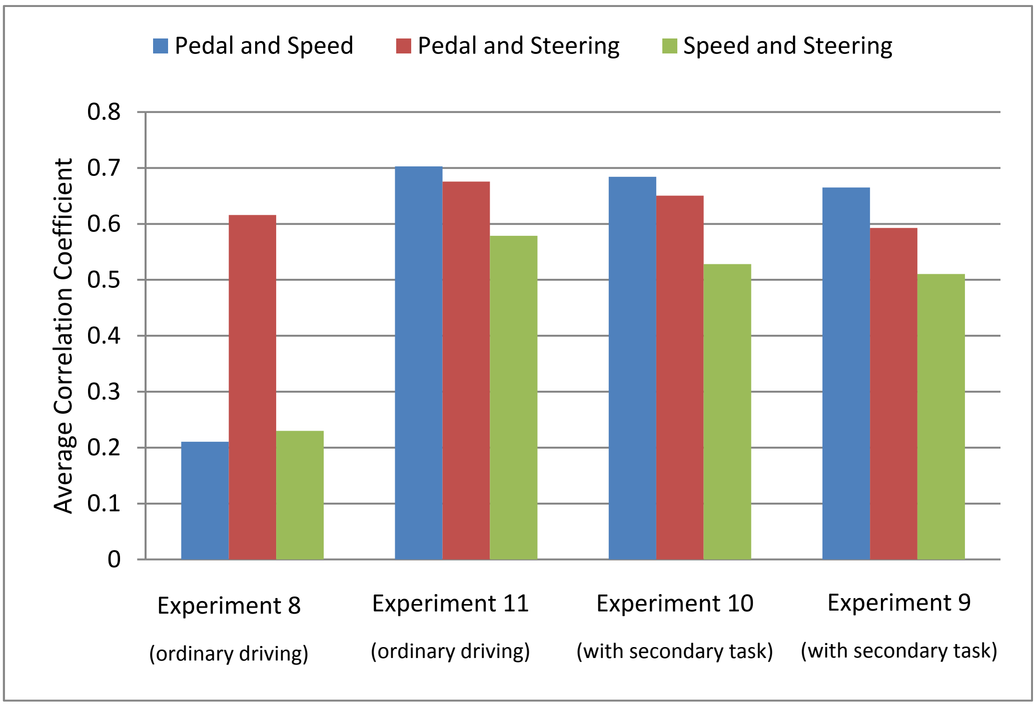


Figure 4.6: Average of correlation coefficient from neutral driving, inattentive driving and neutral driving with sensor error of driver 18

failure. The top figure shows the ped al pressure, the bottom figure shows the steering angle and the middle figure shows the car speed.

Based on the method discussed in Section 4.2.3, faulty sensor diagnosis using the sensor diagnosis module can be realized. At first, offline analysis was performed to determine the average correlation (threshold) value, $\rho_{ij}(\tau)$ of each driver by Equation (4.4) using all driving data from neutral and inattentive driving collected by the working sensor. The average correlation, $\bar{\rho}_{ij}$ for each driver was calculated using equations (4.5). Figure 4.8 shows the average correlation coefficient for four experiments of driver 18. Experiment 8 is neutral driving with a speed sensor failure, experiment 11 is neutral driving, experiment 10 is driving with a music retrieval task and experiment 9 is driving with an alphanumeric repetition task. As can be seen in the figure, the average correlation between the pedal and speed, and speed and steering in the experiment 8 decreases due to the speed sensor failure.

After the threshold value (average correlation), $\bar{\rho}_{ij}$ for each driver has been determined, online in-vehicle sensor diagnosis can be performed. Measurement data from the speed sensor, pedal sensor and steering sensor are input into the sensor diagnosis module. Figure 4.7 shows an example of the diagnosis results of the sensor credibility using highway driving data shown in Figure 2.3 in Chapter 2, and Figure 4.8 shows an example of the diagnosis result of the sensor credibility using driving data on the highway shown in Figure 4.5. Figure 4.7 (a) and 4.8 (a) show the credibility, $R_j(\tau)$ value of each sensor, while Figure 4.7 (b) and 4.8 (b) shows the sensor diagnosis module output. In figure (a), the credibility, $R_j(\tau)$ is evaluated once every second and its magnitude is expressed in binary, either one or zero. In figure (b), the sensor diagnosis module outputs a diagnosis result for each sensor every three seconds. This is because there is a possibility of momentary signal disorders caused by pebbles on the road. As can be seen in Figure 4.7 (b), the sensor diagnosis module can provide good diagnosis results. The sensor credibility of the speed, pedal and steering sensors

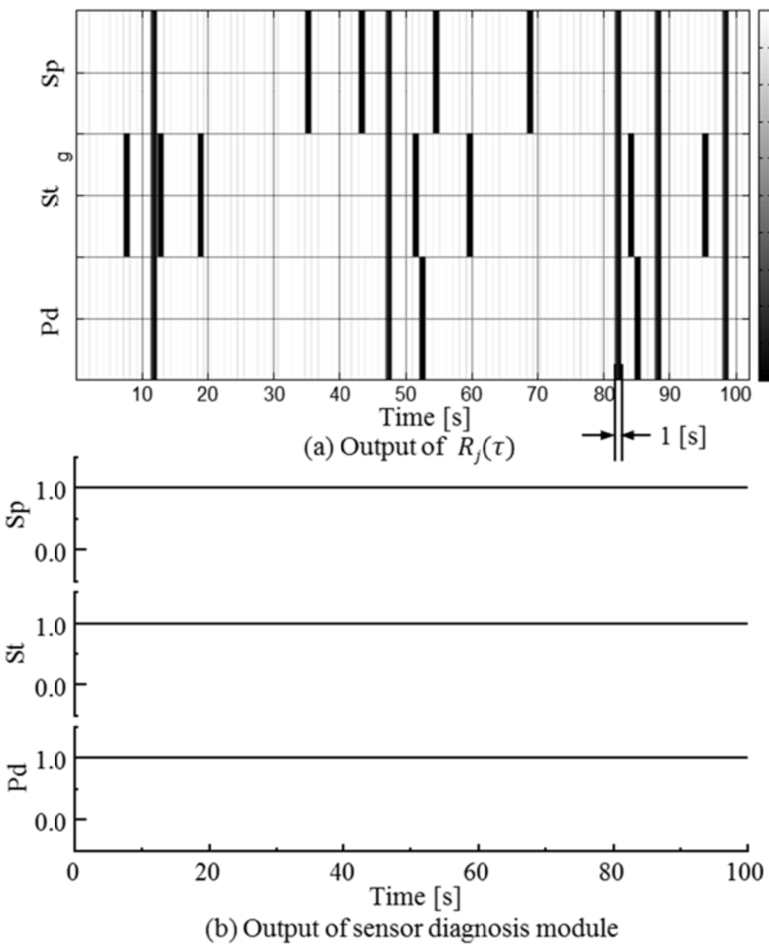


Figure 4.7: Example of sensor detected result obtained by the sensor diagnosis module in the case where all sensors are normal

converged to one for most of the time and indicates that the sensors were working properly. On the other hand, sensor credibility of the speed sensor shown in Figure 4.8 (b) converged to zero and indicates the failure of the sensor. The results show the effectiveness of the proposed in-vehicle sensor diagnosis module. The same result can be obtained from other driving data.

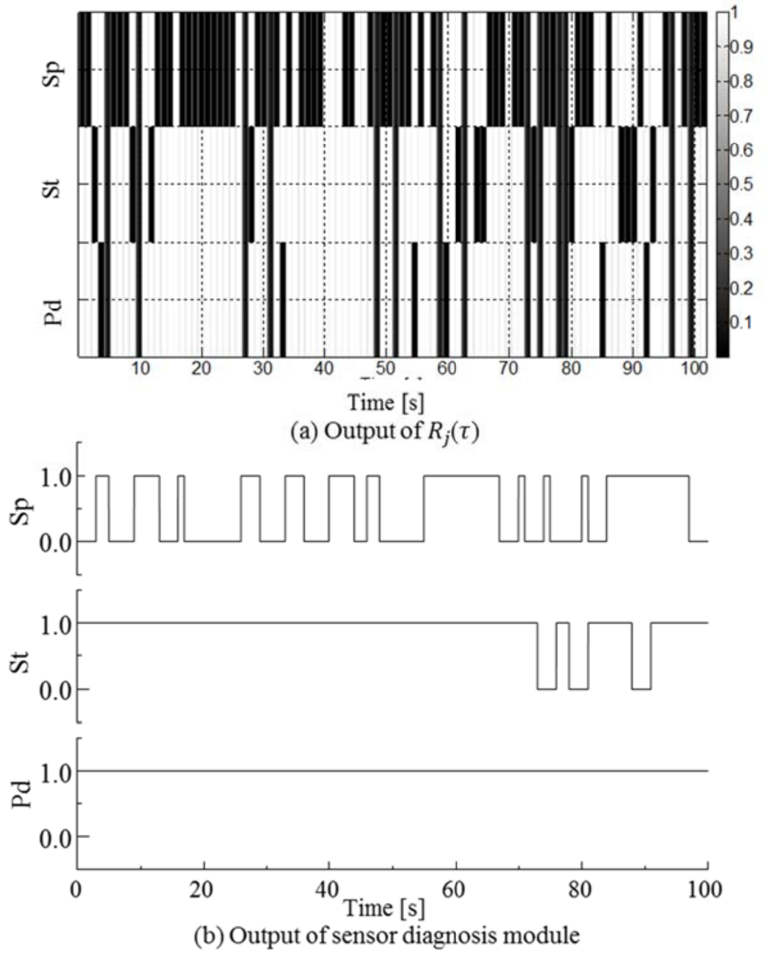
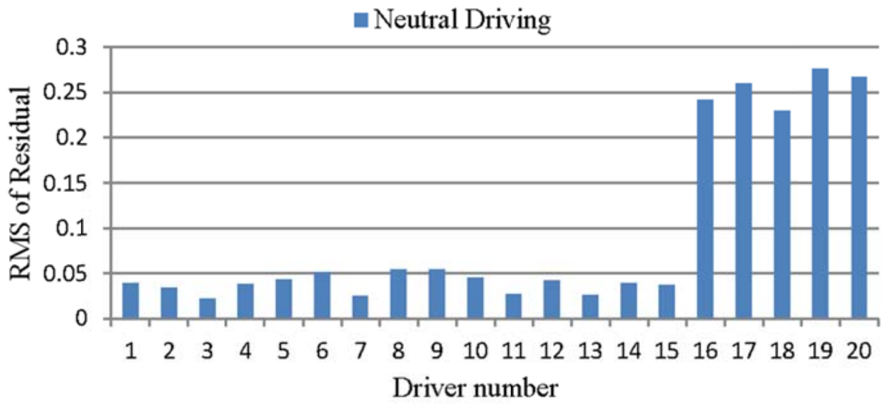


Figure 4.8: Example of sensor detected result obtained by the sensor diagnosis module in the case where speed sensors is faulty

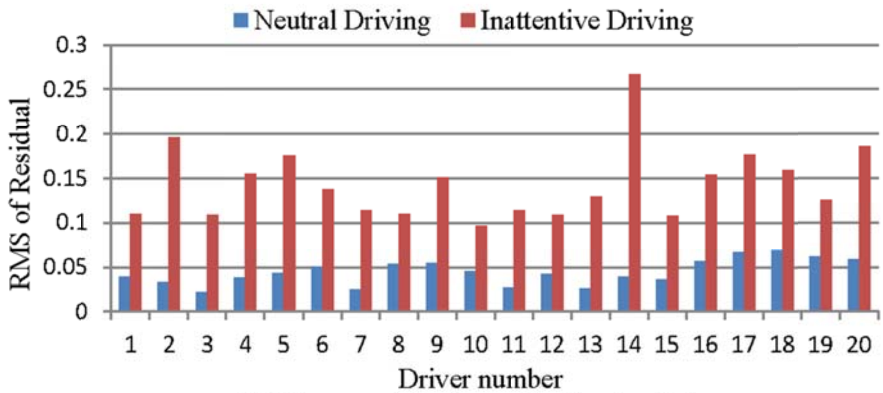
4.3.3 Performance of Driver Inattention Detection System

In order to investigate the effect of sensor failure on the detection result and the effectiveness of this system, we first constructed and trained an individual driver model for 20 drivers. The model's construction and training procedures are the same as those discussed in Sections 3.2 and Section 4.2.4. We used neutral and inattentive driving data from the 20 drivers to test their model, respectively. All sensors (pedal sensor, speed sensor and steering angle sensor) were working properly when collecting driving data for drivers 1 to 15, while one of the sensors that measured data for drivers 16 to 20 were faulty. In other words, we used 15 driving data collected by normal sensors and 5 data collected by a faulty sensors (only one of the sensors was faulty) to study their effects on the detection result. The obtained results are very encouraging, which increased the detection rate and avoided false alarm detection. Figure 4.9 shows output from the driver models when input the neutral and inattentive driving data, where (a) is the output from the old driver model as discussed in Section 3.2 and (b) is the output from the new driver models shown in Section 4.2.4, which are in the driver model part of the inattentive driving detection system. As can be seen from Figure 4.9(a), using the old driver model, the RMS value increased dramatically if one of the sensors was faulty, and produced incorrect detections for drivers 16 to 20. However, with our new proposed driver models, the system can clearly identify neutral driving and inattentive driving even though there was a faulty sensor as shown in Figure 4.9(b). These results confirm the effectiveness of the proposed system.

Figure 4.12 shows the output of the driver inattention detection system, and the confidence score obtained by the inattention detection part from neutral driving (validation process) and inattentive driving data, where the confidence scores are calculated by Equation (4.8). As can be seen, the percentage of the confidence score is very high for the all drivers and is more than 80[%] for the neutral operation, whereas for inattentive operation the score drops below 70[%]. This result indicates the effectiveness of the proposed driver inattention detection system for inattentive driving detection and also shows that the percentage of the confidence score obtained from the inattention detection part can be used to interpret how much the driver is affected by distraction from the given task. Furthermore, the percentage of the confidence score differs for each driver. We think this is due to the fact that the influence of the secondary task for inattentive driving differs based on different driving experiences, and the driver's behaviour.



(a) Old model shown in Section 2.



(b) New models shown in Section 3.4.

Figure 4.9: RMS of residual for neutral driving data and inattentive driving using two different methods

4.4 Conclusions

In this study, in order to monitor the driver's state in the car and to detect inattentive driving, a robust driver inattention detection system by driver model and dynamic relations network (DRN) using sensor data such as the quantity of vehicle speed and pedal operation was proposed. The system can be divided into three parts: the sensor diagnosis module, the driver model and inattention detection. In order to achieve robustness of the system, the sensor diagnosis module by using the DRN was developed to analyze and identify faulty sensors (if any) through its measurement data. In the driver model part, three driver models were developed. Driver model 1 is a normal model that has three input sensors, while driver models 2 and 3 have only two input sensors. The built driver inattention detection system was operated with actual car driving data on a highway and the diagnosis performance was evaluated. As the obtained results, the percentage of the confidence score of system output was very high for the all drivers and was more than 80[%] for the neutral operation residual whereas for inattentive operation the score dropped below 70[%]. This result indicates the effectiveness of the proposed driver inattention detection system for inattentive driving detection.

Chapter 5

Conclusions and Suggestions

5.1 Conclusions

Inattentive driving is a leading cause of motor-vehicle crashes. Developing distraction mitigation systems that adjust their functions to reduce the impairment of distraction according to driver state can help to reduce distraction-related crashes. For such a system, accurately recognizing inattentive driving is critical. To address this need, this study proposed a new robust detection method for inattentive driving caused by cognitive distraction using real driving data.

Accurately identifying driver inattention using real driving data is a critical challenge in developing driver support systems in order to minimize road accidents. However, to our knowledge, most of the previous studies only use data from simulated environment because of the risks of involving inattentive drivers in real situation. While simulator may have some advantage, their reliability is often questionable which makes interpreting results difficult and perhaps not too practical in real driving situation. Numerous previous studies use physiological measures to detect driver inattention. Even though the methods could give accurate result, it requires attachment of devices to the driver, hence not suitable because intrusive to the driver.

Some researchers are study the detection of inattention driver using driving performance measures since this approach have the advantage of being non-intrusive to the driver. However, the detection rate of the proposed method is low and need for the improvement. Furthermore, some of the proposed method uses external signal (e.g. following distance) as one of the inputs to the model, which vulnerable to the external environment such as heavy rain, snow, etc., that will result the system capability to be reduced.

In Chapter 2, the description of experiments and the condition for data collection were discussed. The experiments were performed in real driving situation using real data collected vehicle (DCV). In order to collect inattentive driving data, four secondary tasks have been imposed to distract driver during the experiment. Secondary tasks were used as the source of distraction because it could cause detrimental effect on driving performance. In this study, four secondary tasks have been used: 1) a navigation dialog task, 2) an alphanumeric reading task, 3) a signboard-reading task and 4) a music retrieval task. Based on the driving data collected through the experiment and statistical analysis that has been done, we found that steering angle performance variable has significant effect by to inattentive driving.

A new method to identify driver inattention in driving tasks caused by cognitive distraction was proposed in Chapter 3. The method involved constructing a neural network-based NARX model for each driver using neutral driver operation signals (i.e. without a secondary task). The results obtained show that in the case of neutral driving, the percentage of confidence score for the model residuals is very high and is more than 90[%] whereas in the case of inattentive driving, the score drops below 70[%]. It has been shown that the model is capable of demonstrating the effects of inattention on individual drivers through its residual value. Therefore, by using the proposed method the inattention in driving caused by cognition distraction can be detected, although it is difficult by using traditional method, which focused on detecting inattention caused by fatigue and visual distractions.

In Chapter 4, a robust driver inattention detection system by driver model and dynamic relations network (DRN) using sensor data such as the quantity of vehicle speed and pedal operation was proposed. The system can be divided into three parts: the sensor diagnosis module, the driver model and inattention detection. In order to achieve robustness of the system, the sensor diagnosis module by using the DRN was developed to analyse and identify faulty sensors (if any) through its measurement data. In the driver model part, three driver models were developed. Driver model 1 is a normal model that has three input sensors, while driver models 2 and 3 have only two input sensors. The built driver inattention detection system was operated with actual car driving data on a highway and the diagnosis performance was evaluated. As the obtained results, the percentage of the confidence score of system output was very high for the all drivers and was more than 80[%] for the neutral operation residual whereas for inattentive operation the score dropped below 70[%]. This result indicates the effectiveness of the proposed driver inattention detection system for inattentive driving detection.

The major contribution of this dissertation therefore, is the development and evaluation of a model-based inattentive driving detection method with a novel input sensor diagnosis module, and evaluated on real world driving data.

5.2 Suggestions

Extending from this work, a promising direction is to generate a computational model of human cognitive impairments (distraction, fatigue, and aging) in various behaviour fields. In research on driving, there are three dimensions to extend this research: impairments (e.g., fatigue and alcohol use), sensor technology (e.g., physiological signals), and algorithms (e.g., Dynamical Bayesian Network). Future research could focus on developing and validating real-time detection systems for distraction and fatigue using indicative behavioural predictors and time-series algorithms. It is recommended that future research should focus on comprehensive attention support systems, integrating information from different sensors and not only rely on one type of detection.

Such approaches could also apply to other domains, including Human Computer Interaction (HCI) and medical practice, both of which suffer from cognitive impairments of human operators/practitioners and people might benefit if the computer system could understand and respond to their state.

References

[1] M. Peden, R. Scurfield, D. Sleet, D. Mohan, A.A. Hyder, E. Jarawan and C. Mathers, World Report on Road Traffic Injury Prevention, 3rd ed., Geneva, 2004.

[2] E. D. Sussman, H. Bishop, B. Madnick, and R.Walter, Driver inattention and highway safety, Transp. Res. Rec., no.1047, pp. 40–48, 1985.

[3] J. Wang, R. R. Knipling, and M. J. Goodman, The role of driver inattention in crashes; new statistics from the 1995 crashworthiness data system (CDS), Proc. 40th Annual,: Assoc. Advancement Automotive Med., pp. 377–392, 1996.

[4] Global status report on road safety: time for action. Geneva, World Health Organization, 2009) www.who.int/violence_injury prevention/road_safety_status/2009/en/index.html, accessed 25 January 2013.

[5] Global burden of disease, 2008. Geneva, World Health Organization, 2011 (http://www.who.int/healthinfo/global_burden_disease/estimates_regional/en/index.html, accessed 22 February 2013).

[6] G. Jacobs, A. Aeron-Thomas. Estimating global road fatalities. Crowthorne, Transport Research Laboratory, 2000.

[7] J. C. Stutts, D. W. Reinfurt, L. Staplin, and E. A. Rodgman, The role of driver distraction in traffic crashes, AAA Foundation of Traffic Safety, 2001.

[8] European Project FP6 (IST-1-507674-IP), AIDE – adaptive integrated driver-vehicle interface, [online]. Available: http://www.aide-eu.org/index.html. 2004–2008.

[9] AAA Foundation for Traffic Safety, The Role of Driver Distraction in Traffic Crashes, http://www.aaafoundation.org/pdf/distraction.pdf, May 2001.

[10] J. D. Lee, Driving safety: Review of Human Factors. Santa Monica, CA: Human Factors and Ergonomics Society. (2006).

[11] J. R. Treat, N. S. Tumbas, S. T. McDonald. Tri-level study of the causes of traffic accidents (No. DOT-HS-034-3535-77): Indiana University. (1977).

[12] M. Miyaji, M. Danno and K. Oguri, Analysis of driver behavior based on traffic incidents for driver monitor systems. 2008 IEEE Intelligent Vehicles Symposium, pp. 930-935, 2008.

[13] M. Hamada. Analysis of Traffic Accident Trend in Japan and Predictions for the Future", Review of Automotive Engineering, Vol. 27, pp. 1-6, 2006.

[14] National Police Agency in Japan, "Road Traffic Accidents in 2006", February 25, 2007.

[15] M. Kaneda, et al. Development of a drowsiness warning system, 11th Int. Conf. Enhanced Safety of Vehicles,1994.

[16] H. Ueno, M. Kaneda, and M. Tsukino, Development of drowsiness detection system, Proc. Vehicle Navigation and Information Systems Conf., pp.15-20 1994.

[17] W. Wierwille, Overview of research on driver drowsiness definition and driver drowsiness detection, 11th Int. Conf. Enhanced Safety of Vehicles, 1994.

[18] L. M. Bergasa, J. Nuevo, M. A. Sotelo, R. Barea and M. E. Lopez, Real-Time System for Monitoring Driver Vigilance, IEEE Transaction on Intelligent Transportation Systems, Vol. 7, Issue 1, pp. 63-77, 2006.

[19] S. G. Klauer, T. A. Dingus, V. L. Neale, J. D. Sudweeks, & D. J. Ramsey, The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data, 2006.

[20] National Highway Traffic Safety Administration (NHTSA), Distracted Driving 2010 (DOT HS 811 650). Washington DC, 2012.

[21] T.A. Ranney, Driver distraction: A review of the current state-of-knowledge, 2008.

[22] A. J. McKnight and A. S. McKnight, The effect of cellular phone use upon driver attention, Accident Anal. Prev., vol. 25, no. 3, pp. 259–265, 1993.

[23] D. L. Strayer and W. A. Johnston, Driven to distraction: dual-task studies of simulated driving and conversing on a cellular telephone, Psychol. Sci., vol.12, no.6, pp. 462–466, 2001.

[24] P. Jiménez, L.M. Bergasa, J. Nuevo, Gaze Fixation System for the Evaluation of Driver Distractions Induced by IVIS, Intelligent Transportation Systems, IEEE Transactions on , vol.13, no.3, pp.1167-1178, Sept. 2012.

[25] M.M. Bundele, R. Banerjee, An SVM Classifier for Fatigue-Detection Using Skin Conductance for Use in the BITS-Lifeguard Wearable Computing System, Emerging Trends in Engineering and Technology (ICETET), 2009 2nd International Conference on , vol., no., pp.934-939, 16-18 Dec. 2009.

[26] E. A. Byrne, R. Parasuraman, Psychophysiology and adaptive automation. Biological Psychology, pp.249-268, 1996.

[27] B. Thomas Jap, S. Lal, P. Fischer and E. Bekiaris, Using EEG spectral components to assess algorithms for detecting fatigue, Expert Systems with Applications, vol.36, issue 2, pp.2352-2359, 2009.

[28] C. Papadelis, Non-linear analysis for the sleepy drivers problem, MEDINFO, vol.12, issue Pt 2, pp. 1294-1298, 2007.

[29] V.M. Yeo, X. Li et al., Can SVM be used for automatic EEG detection of drowsiness during car driving?, Safety Science, vol. 47, issue 1, pp.115-124, 2009.

[30] K.Q. Shen, X.P. Li, et al. EEG-based mental fatigue measurement using kulti-class support vector machines with confidence estimate, Clinical Neurophysiology, vol. 119, pp.1524-1533, 2008.

[31] C.T. Lin, R.C. Wu, EEG-based drowsiness estimation for safety driving using independent component analysis, Circuits and Systems I: Regular Papers, vol. 52, issue 12, pp. 2726 - 2738, 2005.

[32] C.P. Chua, G. McDarby and C. Heneghan, Combined electrocardiogram and photoplethysmogram measurements as an indicator of objective sleepiness, Physiological Measurement, vo1.29, pp.857-868, 2008.

[33] D. Dinges, F. Perclos, A valid psychophysiological measure of alertness as assessed by psychomotor vigilance, Federal Highway Administration. Office of motor carriers, Tech. Rep. MCRT-98-006, 1998.

[34] C.T. Lin, R. Wu, EEG-based drowsiness estimation for safety driving using independent component analysis, Circuits and Systems I: Regular Papers, vol. 52, issue 12, pp. 2726 - 2738, 2005.

[35] J. Sloten, et al., Development of neckband mounted active bio-electrodes for non-restraint lead method of ECG R wave," in 4th European Conference of the

International Federation for Medical and Biological Engineering. vol. 22, R. Magjarevic, Ed., ed: Springer Berlin Heidelberg, pp. 1394-1397, 2009.

[36] A. Moriguchi, et al., "Spectral change in heart rate variability in response to mental arithmetic before and after the beta-adrenoceptor blocker, carteolol," Clinical Autonomic Research, vol. 2, pp. 267-270, 1992.

[37] J. Östlund, et al., "Deliverable 2—HMI and safety related driver performance," GRD1/2000/25361S12.319626, 2004.

[38] M. Akin, et al., "Estimating vigilance level by using EEG and EMG signals," Neural Computing & Applications, vol. 17, pp. 227-236, 2008.

[39] A. Santana Diaz, et al., "Driver hypo-vigilance diagnosis using wavelets and statistical analysis," in 5th IEEE International Conference on Intelligent Transportation Systems, pp. 162-167, 2002.

[40] E. Kawakita, et al., "Estimation of driver's mental workload using visual information and heart rate variability," in 13th International IEEE Conference on Intelligent Transportation Systems, pp. 765-769, 2010.

[41] J. Engström, et al., "Effects of visual and cognitive load in real and simulated motorway driving," Transportation Research Part F: Traffic Psychology and Behaviour, vol. 8, pp. 97-120, 2005.

[42] J. Laberge, et al., "Effects of Passenger and Cellular Phone Conversations on Driver Distraction," Transportation Research Record: Journal of the Transportation Research Board, vol. 1899, pp. 109-116, 2004.

[43] J. L. Harbluk, et al., "An on-road assessment of cognitive distraction: Impacts on drivers' visual behavior and braking performance," Accident Analysis & Prevention, vol. 39, pp. 372-379, 2007.

[44] S. Benedetto, et al., "Driver workload and eye blink duration," Transportation Research Part F: Traffic Psychology and Behaviour, vol. In Press, Corrected Proof, 2010.

[45] Y. Liang and J. D. Lee, "Combining cognitive and visual distraction: Less than the sum of its parts," Accident Analysis & Prevention, vol. 42, pp. 881890, 2010.

[46] S. Dhar, et al., "Implementation of real time Visual Attention Monitoring algorithm of human drivers on an embedded platform," in Students' Technology Symposium (TechSym), 2010 IEEE, pp. 241-247, 2010.

[47] C. Owsley, K. Ball, G. McGwin, Visual processing impairment and risk of motor vehicle crash among older adults. Journal of the American Medical Association, 279(14), pp.1083-1088, 1998.

[48] Y.-C.Lee, J. D. Lee, Visual attention in driving: The effects of cognitive load and visual disruption. Human Factors, 49(4), pp.721-733, 2007.

[49] J.-M. Hoc, Towards a cognitive approachto human-machine cooperation in dynamic situations. International Journal of Human-Computer Studies, 2001.

[50] M. Yang, D. Kriegman, and N. Ahuja, Detecting paces in images: A Survey, IEEE Trans. Pattern Anal. Machine Intell., vol.24, no.1, pp. 34–58, 2002.

[51] Z. Zhu and Q. Ji, Real time 3D face pose tracking from an uncalibrated camera, proc. of CVPR Workshop, pp. 73–80, 2004.

[52] E. Murphy-Chutorian, A. Doshi, and M. M. Trivedi, Head pose estimation for driver assistance systems: a robust algorithm and experimental evaluation, Proceedings of ITSC, pp. 709–714, 2007.

[53] N. Ikoma, Y. Miyahara and H. Maeda, Tracking of feature points in dynamic image with classification into objects and 3D reconstruction by particle filters, Special Issue of International Journal of Innovative Computing, Information and

Control on Fuzzy Systems & Innovational Computing, vol.2, no.1, pp.167-180, 2006.

[54] X.Fan, B.Yin and Y.Sun, Yawning Detection for Monitoring Driver Fatigue, Proceeding of the Sixth International Conference on Machine Learning and Cybernetics, 2007.

[55] W-H. Dong, X-J Wu, "Driver Fatigue Detection Based on the Distance of Eyelid" , IEEE Int. Workshop VLSI Design & Video Tech Suzhou, China, May 28-30, 2005.

[56] M. Suzuki, N. Yamamoto, K. Yamada, O. Yamamoto, T. Nakano, S. Yamamoto, Presuming the Driver's Drowsiness by Image Processing and a trial of Application to a Driving Support System, IEEJ Transactions on Electronics, Information and System, Vol.126, No.12, pp.1497-1502, 2006.

[57] T. Pilutti, A.G. Ulsoy, Identification of driver state for lane-keeping tasks, Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on , vol.29, no.5, pp.486,502, Sep 1999.

[58] H. Ishikawa, C. Miyajima, N. Kitaoka and K. Takeda, Detection of distracted driving using a Bayesian network, ICIC Express Letter, Part B: Applications, vol.2, no.2, pp.621-626, 2011.

[59] Y. Kuroyanagi, C. Miyajima, N. Kitaoka and K. Takeda, Analysis and detection of potentially hazardous driving situations, ICIC Express Letter, Part B: Applications, vol.2, no.2, pp.627-633, 2011.

[60] Othman Md Rizal, Z. Zhang, T. Imamura, T. Miyake, Modeling driver operation behavior by linear prediction analysis and auto associative neural network, Proc. of The 2009 IEEE Int. Conference on Systems, Man, and Cybernetics (IEEE SMC2009), San Antonio USA, pp.655-659, 2009.

[61] Md Rizal Othman, Zhong Zhang, Takashi Imamura and Tetsuo Miyake, Driver Innat-tention AnalysisUsing Network Based Nonlinear ARX Model, ICIC Express letters, Part B: Applications, Vol.2,No.3, pp.679-686, 2011.

[62] Md Rizal Othman, Zhong Zhang, Takashi Imamura and Tetsuo Miyake, A Novel Method for driver Inattention Detection Using Driver Operation Signals , International Journal of Innovative Computing, Information and Control, Vol.8, No.4, pp.2625-2636, 2012.

[63] T. W. Victor, Keeping eye and mind on the road. Unpublished Doctoral thesis, Uppsala Universitet, Uppsala: Uppsala University, Interfaculty Units, Acta Universitatis Upsaliensis. (2005).

[64] J. F. K M.Baumann, Situation awareness and driving: A cognitive model. In Pietro C. Cacciabue (Ed.), Modelling driver behaviour in automotive environments: Critical issues in driver interactions with intelligent transport systems, pp. 253, (2007).

[65] G.Hole, Perceptual factors in driving. The psychology of driving, Lawrence Earlbaum Associates, pp.20, 2007.

[66] M. Miyaji, M. Danno, Driver's cognitive distraction detection using AdaBoost on pattern recognition basis. Proceedings of the 2008 IEEE International Conference Vehicular Electronics and Safety, Columbus, OH, USA. 51. 2008.

[67] Y. Liang, J.D. Lee, M.L. Reyes, Nonintrusive detection of driver cognitive distraction in real time using Bayesian networks. Transportation Research Record: Journal of the Transportation Research Board.

[68] D. Haigney and S. J. Westerman, Mobile (cellular) phone use and driving: A critical review of research methodology, Ergonom., vol. 44, no.2, pp. 132–143, 2001.

[69] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, Driver inattention monitoring system for intelligent vehicles: a review, IEEE Transactions on Intelligent Transportation Systems, vol. 12, no. 2,pp. 596–614, 2011.

[70] N. Kawaguchi, S. Matsubara, K. Takeda, and F. Itakura, Multimedia data collection of in-car speech communication, in Proc. 7th Eur. Conf. Speech Commun. Technol., pp. 2027–2030, Sep. 2001.

[71] M. A. Regan, J. D. Lee, and K. L. Young, Driver Distraction: Theory,Effects, and Mitigation. Boca Raton, FL: CRC, 2009.

[72] J. C. Stutts, D. W. Reinfurt, L. Staplin, and E. A. Rodgman, The Role of Driver Distraction in Traffic Crashes. Chapel Hill, NC: Univ. North Carolina Highway Safety Res. Center, 2001.

[73] M. Rakauskas and N. Ward, Behavioral Effects of Driver Distraction and Alcohol Impairment, Proc. 49th Annual Meeting Human Factors Ergonomics Soc., pp. 1912–1916, 2005.

[74] Nieminen and H. Summala, Novice and Experienced Drivers' Looking Behavior and Primary Task Control While Doing a Secondary Task, Proc. 38th Annual Meeting Human Factors Ergonomics Soc., vol. 2, pp. 852–856, 1994.

[75] T. A. Ranney, E. N. Mazzae, W. R. Garrott, and F. S. Barickman, Development of a Test Protocol to Demonstrate the Effects of Secondary Tasks on Closed-course Driving Performance," Proc. 45th Annual Meeting Human Factors Ergonomics Soc., 2001, pp. 1581–1585.

[76] B. H. Kantowitz, R. J. Hanowski, and L. Tijerina, Simulator Evaluation of Heavy-vehicle Driver Workload, Part II: Complex secondary tasks, in Proc. 40th Annual Meeting Human Factors Ergonomics Soc., vol. 2, pp.877–881, 1996.

[77] T. A. Ranney, J. L. Harbluk, and Y. I. Noy, The Effects of Voice Technology on Test Track Driving Performance: Implications for Driver Distraction, in Proc.

Human Factors Ergonomics Soc. Conf., pp.1814–1818, 2002.

[78] C.A. Pickering, K.J. Burnham, M.J. Richardson, A Review of Automotive Human Machine Interface Technologies and Techniques to Reduce Driver Distraction, System Safety, 2nd Institution of Engineering and Technology International Conference, pp.223-228, 22-24 Oct. 2007.

[79] D. McLean, T.P. Newcomb, and R.T. Spurr, Simulation of Driver Behavior During Braking, In Proceedings of the International Mechanical Engineers Conference on Braking of Road Vehicles, 1976.

[80] T.P. Newcomb, Driver Behavior During Braking, In Proceedings of the SAE West Coast International Meeting, Seattle, 1981.

[81] K. Rompe, M. Wallrich, and A. Schindler, Advantages of Anti Wheel Lock System (Abs) for the Average Driver in Difficult Driving Situations, Thermotech. Assoc. Tuscany; Univ. Florence, Italy, 1987.

[82] P. Fancher, and Z. Bareket, Evolving Model for Studying Driver–Vehicle System Performance in Longitudinal Control of Headway, Transportation Research Record 1631, pp. 13–19, 1998.

[83] H. Peng, Evaluation of Driver Assistance Systems – a Human Centred Approach, Proceedings of the 6th International Symposium on Advanced Vehicle Control (AVEC), Japan, 2002.

[84] P.G. Gipps, A Behavioral Car-Following Model for Computer Simulation, Transportation Res. B.15, pp. 105–111, 1981.

[85] T.J. Harris and W. Yu, Controller Assessment for a Class of Nonlinear Systems, Journal of Process Control, vol.17, pp. 607-619, 2007.

[86] M. I. A. Lourakis, A Brief Description of the Levenberg-Marquardt Algorithm, Technical Report, Institute of Computer Science, Foundation for Research and Technology, Hellas, 2005..

[87] D. W. Marquardt, An Algorithm for Least Squares Estimation of Nonlinear Parameters, SIAM J. Appl. Math., vol.11, pp. 431-441, 1963.

[88] M.T. Hagan, M.B. Menhaj, Training Feedforward Networks with the Marquardt Algorithm, IEEE Trans. Neural Network, vol.5, no.6, pp. 989-993, 1994.

[89] S. Li, and Y. Chen, Sensor Fault Detection for Manufacturing Quality Control, MIE Department Rep. No. MIE-2006-01, Univ. of Iowa, Iowa City, Iowa, 2006.

[90] S. Simani, C. Fantuzzi, and S. Beghelli, Diagnosis Techniques for Sensor Faults of Industrial Processes, IEEE Transactions on Control Systems Technology, 1999.

[91] A. B. Sharma, L. Golubchik, R. Govindan, Sensor Faults: Detection Methods and Prevalence in Real-World Datasets, ACM Transactions on Sensor Network (TOSN), Vol. 6, No. 3, pp. 1–34, June 2010.

[92] T. Oates, Fault Identification in Computer Network: A Review and a New Approach, University of Massachusetts Amherst, Tech. Rep. UM-CS1995-113, 1995.

[93] P. Jalote, Fault Tolerance in Distributed Systems. Englewood Cliffs. NJ: Prentice-Hall, 1994.

[94] J. J. Gertler, Survey of Model-based Failure Detection and Isolation in Complex Plants, IEEE Control Systems Magazine, vol. 12, no. 6, pp.3–11, 1988.

[95] R. Isermann, Process Fault Detection based on Modeling and Estimation Method - A Survey," Automatica, no. 20, pp. 387–404, 1984.

[96] A. Willsky, A Survey of Design Methods for Failure Detection in Dynamic Systems, Automatica, no. 12, pp. 601–611, 1976.

[97] K. Yamada, T. Ito, An Approach to Understanding of Driving Environment Using the Network Typed Sensor Fusion Method, IEICE Transactions of the

Institute of Electronics, Information and Communication Engineers D-II, Vol.J86-D-II, No.2, pp.223-232, 2003.

[98] Y. Ishida, Francois Mizessyn, Sensor Diagnosis of Process Plants by an Immune-Based Model, Transactions of Systems, Control and Information Engineers, Vol.7, No.1, pp.1-8, 1994.

[99] F. P. Preparata, G. Metze, and R. T. Chien, On the Connection Assignment Problem of Diagnosable Systems, IEEE Trans. Computer, EC-16, pp.848-854, 1967.

[100] Y. Watanabe, Y. Ishida, Immunity-Based Approaches for Self-Monitoring in Distributed Intrusion Detection System. In Knowledge-Based Intelligent Information and Engineering Systems, Springer, Berlin, Germany, (LNCS Part 2), pp. 503-510, 2003.

[101] C.A. Laurentys, R.M. Palhares, W.M. Caminhas, Design of an Artificial Immune System Based on Danger Model for Fault Detection, Expert Systems with Applications, Expert Syst. Appl. Int. J., Vol. 37, pp. 5145-5152, 2010.

[102] N.K. Jerne, The Immune System. Sci. Amer., pp. 52-60, 1973.

[103] Y. Ishida, Immunity-Based Systems: A Design Perspective, Springer-Verlag, New York, NY, USA, 2004.

Acknowledgments

I would like to give special thanks to Professor Dr. Zhong ZHANG for his invaluable advice, guidance, and tireless support from the very first time I came to Toyohashi of Technology (TUT). He provided an important source of ideas, motivation and criticism from the beginning of my study.

I would like to express my sincere gratitude to Professor Dr. Yoshiaki SHIMIZU, Associate Professor Dr. Tetsuo MIYAKE and Associate Professor Takanori MIYOSHI for their patience in reviewing this thesis, valuable discussion and pertinent discussion to finish this work.

I must thank to Dr. Takashi IMAMURA, who has been a great mentor all these years especially when I was at a loss in this study. I appreciate his gentleness and kindness.

I would like to thank members in Instrumentation Systems Laboratory, and administrative staff at Department of Electrical and Electronic Information Engineering and Department of Mechanical Engineering, that made my life at TUT an enjoyable experience.

I would like to thank my colleagues over these years; whose have provided support, conversation, and help. I would like to include their name, but they are too many to list.

Finally, I wish I knew a better way to express my indebtedness to my wife, Zaitisafina, my sons and daughters, for their unconditional support, endless love, to my parents for their encouragement and inspiration throughout my life that helped me outgrow again and again.

Last but not least, I gratefully acknowledge to the Global COE program "Frontier of Intelligent Sensing", Toyohashi University of Technology and Ministry of Education, Culture, Sport, Science and Technology (MEXT), JAPAN, DENSO and HORI Foundation for supporting this work. The authors also gratefully acknowledge the supply of driving data, which was collected by Takeda Laboratory, Nagoya University.

September 9, 2013

MD Rizal Othman

Publications

Paper with referee's review published in journal

1. **Md Rizal Othman**, Zhong Zhang, Takashi Imamura and Tetsuo Miyake, A Novel Method for Driver Inattention Detection Using Driver Operation Signals, International Journal of Innovative Computing, Information and Control, Vol. 8, No. 4, pp.2625-2636 (2012).
2. **Md Rizal Othman**, Zhong Zhang, Takuma Akiduki, Hajime Suzuki, Takashi Imamura and Tetsuo Miyake, Development of a Driver Inattention Detection System using Dynamic Relational Network, International Journal of Innovative Computing, Information and Control, (Accepted).

Paper with referee's review published in letters

1. **Md Rizal Othman**, Zhong Zhang, Takashi Imamura and Tetsuo Miyake, Driver Inattention Analysis Using Neural Network Based Nonlinear ARX Model, ICIC Express letters, Part B: Applications, Vol. 2, No. 3, pp.679-686 (2011).
2. **Md Rizal Othman**, Zhong Zhang, Takashi Imamura and Tetsuo Miyake, Analysis and Evaluation of Driver Inattention Using Support Vector Machine, ICIC Express letters, Vol. 6, No. 6, pp.1453-1458(2012).

Papers presented in international conference

1. **Md Rizal Othman**, Zhong Zhang Takashi Imamura and Tetsuo Miyake, A Study of Analysis Method for Driver Features Extraction, Proceedings of 2008 IEEE International Conference on System, Man and Cybernetics (SMC2008, Oct.12-15, Singapore), pp.1501-1505 (2008)
2. **Md Rizal Othman**, Zhong Zhang, Takashi Imamura, Tetsuo Miyake,

Modeling Driver Operation Behavior by Linear Prediction Analysis and Auto Associative Neural Network, Proceeding of The 2009 IEEE International Conference on Systems, Man, and Cybernetics (SMC2009, Oct.11-15, San Antonio USA), pp.649-653 (2009).

Other Publications

1. Takashi Imamura, Hagito Yamashita, Zhong Zhang, **Md Rizal Othman** and Tetsuo Miyake, A Study of Classification for Driver Conditions using Driving Behaviors, Proceedings of 2008 IEEE International Conference on System, Man and Cybernetics (SMC2008, Oct.12-15, Singapore), pp.1506-1511(2008).
2. Takashi Imamura, Hagito Yamashita, **Md Rizal Othman**, Zhong Zhang and Tetsuo Miyake, Driving Behavior Classification and Driver Sensing based on Vehicle Steering Wheel Operations, Proceeding of The SICE Annual Conference 2008, (SICE2008, August 20-22, Tokyo, Japan), pp.2714-2718(2008).
3. Takashi Imamura, Zhong Zhang, Tetsuo Miyake, **Md Rizal Othman**, Development of a Sensor System for Grasp Behavior on a Steering Wheel, Proceeding of The 2009 IEEE International Conference on Systems, Man, and Cybernetics(SMC2009, Oct.11-15, San Antonio USA), pp.250-254(2009).
4. **Md Rizal Othman**, Zhong Zhang, Takashi Imamura and Tetsuo Miyake, A New Methodology For Driver Inattention Detection Through Model Based Analysis, 豊橋技術科学大学グローバル COE 第３回センシングアーキテクト・シンポジウム ADIST2010 講演抄録集, pp.76（2010.10.21）.
5. **Md Rizal Othman**, Zhong ZHANG, Takashi IMAMURA, Tetsuo MIYAKE, 自動車内記録データを用いた運転行動とその安全性の解析，国立大学法人 豊橋技術科学大学グローバル COE プログラム”センシングアーキテクト”による最先端「インテリジェントセンシング研究開発」事例集, pp.28（2009.11.5）.

6. **Md Rizal Othman**, Zhong ZHANG, Takashi IMAMURA, Tetsuo MIYAKE, Analysis of Driver Operation Signal for Abnormal Driving Behavior Detection and Classification，豊橋技術科学大学グローバル COE 第二回学生主催シンポジウム ADIST2009 講演抄録集，pp.80（2009.09.04）.
7. **Md Rizal Othman**，Zhong ZHANG，Takashi IMAMURA，Tetsuo MIYAKE and Hagito YAMASHITA, 線形予測分析と自己想起型ニューラルネットワークによるドライバ個性のモデリング, 第２回”センシングアーキテクト”による発表会 最先端インテリジェントセンシング研究開発，pp76-77, (2009.03.04).
8. 今村孝, **Md Rizal Othman**，章 忠，三宅哲夫，山下萩人，運転行動を用いたドライバ特徴抽出，第８回未来ビークルリサーチセンターシンポジウム，一般講演，pp.24（2008.11.07）.
9. 山下萩人，今村孝，**Md Rizal Othman**，章 忠，三宅哲夫，自動車運転時交差点通過行動における逸脱性検出の検討，自動車技術会 2008 年秋季大会 学術講演会前刷集 No.105-08，pp.1-4 (2008.10.22-24）.
10. **Md Rizal Othman**, Zhong Zhang, Takashi Imamura, Tetsuo Miyake and Hagito Yamashita, A Study of Analysis Method for Driver Features Extraction, 豊橋技術科学大学 グローバル COE ADIST2008，pp.70（2008.10.17）.
11. **Md Rizal Othman**，Study of Analysis Method for Driver Features Extraction，第４回グローバル COE 学生ゼミナール，（2008.06.11）.
12. 山下萩人，今村孝，**Md Rizal Othman**，章 忠，三宅哲夫，運転時ハンドル操作行動による自動車運転逸脱性検出に関する研究，日本機械学会ロボティクス・メカトロニクス部門講演会（ROBOMEC2008），pp.1A1-I15(1)-(2)（2008.06.05-07）.
13. **Md Rizal Othman**，Zhong Zhang，Takashi IMAMURA，Tetsuo MIYAKE，Keisuke ITOH，Hagito YAMASHITA，Study of Abnormal Driving Behavior Detection and Classification Method using In-Vehicle Driving Data，国立大学法人 豊橋技術科学大学グローバル COE”センシングアーキテクト”による最先端「インテリジェントセンシング研究開発」事例集，pp.58-59(2008.03.04).