International Journal of Innovative Computing, Information and Control
Volume **8**, Number **4**, April **2012**
ICIC International ©2012 ISSN 1349-4198
pp. 2625–2636

A NOVEL METHOD FOR DRIVER INATTENTION DETECTION USING DRIVER OPERATION SIGNALS

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Received January 2011; revised May 2011

Abstract. *This paper presents a new methodology for the analysis of driver inattention using the driving operation signals. The proposed method constructs a driver model based on a nonlinear autoregressive exogenous input (NARX) model using neutral driving data. The nonlinear function of the model is approximated by a multilayer perceptron (MLP) neural network. Driving data with and without a secondary task, collected using a real vehicle in Nagoya city, was used in this study. The performance of the model was evaluated during a validation process where the model produced acceptably small errors and the predicted values closely following the actual values. Finally, through an assessment of the model residuals between the actual signal and predicted signal of the inattentive driving data, we prove that driver inattention while driving in a real environment can be detected.*

Keywords: Driver model, Driver inattention, Nonlinear ARX, Multilayer perceptron

1. **Introduction.** Traffic accidents are a serious global problem causing not only a high number of deaths but also economic losses [1]. It has been reported that in 2002 roughly 1.2 million people died as a result of traffic accidents. In addition, more than 20 million people around the world are injured or disabled each year. From an economic perspective, the damage cost of road accidents has been estimated at US$518 billion in 2004 and has been increasing every year. Various studies on causal factors of traffic accidents concluded that driver inattention is a primary cause accounting for more than 25% of accidents [2-6]. The increasing implementation of in-vehicle infotainment systems (IVIS) such as navigation systems, entertainment devices, real-time information systems and communication equipment in modern automobiles along with typical personal tasks such as eating and talking to passengers has exaggerated the problem [7-9].

One promising solution for this problem is to detect and estimate the driver's condition in real time and then use the information together with advanced driver support systems (ADSS) to compensate the effects of inattention or redirect the driver's focus on the main driving tasks. Until now, numerous approaches and methods have been employed by the research community for monitoring and detection of driver inattention. These approaches can be broadly divided into two groups: physiological measures [10-15] and computer vision approaches [16-20]. Physiological measures utilize biological signals such as the EOG, EEG and ECG, which are collected through electrodes contacting the human body. However, these methods always require an attachment of devices to the driver, which is impractical in real driving situations. The latter approach, computer vision, is more practical as it is non-intrusive to the driver. Nevertheless, most of the techniques described above focused on detecting inattention caused by fatigue and visual distractions. Inattention caused by the driver's mental state or driver cognition has been defined and explored much less.

On the other hand, Ishikawa et al. [21] proposed a method to detect driving with secondary tasks using driving behavior signals modeled with a Bayesian network, while taking driving situations into consideration. 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 are imposed on a driver in addition to vehicle operation, such as calculation, talking on a cell phone and looking at road signs. Kuroyanagi et al. [22], furthermore, analyzed hazardous situations in actual driving situations and drivers' responses to hazards, and confirmed that drivers' reactions decrease while driving with secondary tasks. Therefore, the secondary tasks were considered a good tool for creating a driver's inattention state caused by the driver's cognition during actual driving.

In this paper, we propose a new method to detect inattention in driving caused by cognition distraction. The method involves constructing a neural network-based model for each driver using the neutral driver operation signals (i.e., without secondary tasks). Finally, through evaluation of the model residuals, we prove that driver inattention while driving in a real environment with secondary tasks can be detected.

2. **A New Methodology for Measuring Driver Inattention.** It is well accepted that driving performance will degrade when driving with some secondary tasks. 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.

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. The performance degradation therefore can be detected by the presence of operation signals that differ from the normal (neutral) driving signals and which have some turbulence. We here first define driving with turbulent operation signals from the normal (neutral) driving as inattentive driving and driving operation signals without turbulence or with little turbulence as neutral driving. Then, by analyzing the differences between neutral and inattentive driving in terms of driving performance, it is possible to detect driver inattention. In order to achieve the above objective, our approach is comprised of the following steps:

Step 1: An experiment is performed to collect driving operation signals both with and without a secondary task. Driving without the secondary task is considered neutral driving of the driver.

Step 2: A driver model is constructed for each driver using the neutral driving operation signals. This model serves as a baseline model for a particular driver. The baseline model can be improved through an incremental learning process using neutral operation signals.

Step 3: The baseline model is used to predict the model output when given the model inputs. The predicted output should be nearly equal (or equal) to the actual signal if the input signal is taken from neutral driving and vice versa. Driver inattention is examined evaluated through the model's residual between the actual signal and predicted signal.

3. **Experiment Description.** The driving date utilized in this study was 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) an alphanumeric reading task, 3) a signboard-reading task and 4) a music retrieval task. Figure 1 shows the course map used in this study, where mark (1) denotes the start location, marks (2) to (7) and (12) to (13) denote the city roads and marks (8) to (11) denote the highway roads. Table 1 shows all twelve portions of the experiments that correspond to numbers (2) to (13) shown in Figure 1, the types of roads and their conditions during the data collection.

FIGURE 1. The course map used in this study

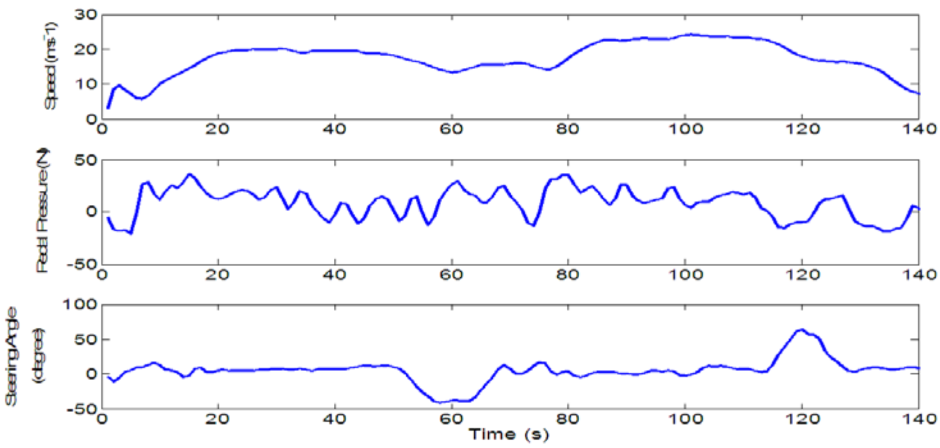
TABLE 1. Description of experiments and driving conditions

Experiment	Type of	Task	Description
1	–	Idling	
2	City	Ordinary riving	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	

In this paper, however, the operation signals of experiments 8, 11 (without secondary task) and 9 (with secondary task) from 15 licensed drivers (eight males and seven females) were selected as examples, in order to investigate the influence of the secondary task to the driver performance and confirm the difference between inattentive driving and neutral driving. An example of driving data that was measured in experiment 8 is shown in Figure 2, where (a) shows the outside image of the car, (b) shows the facial image of a driver and (c) shows the operation signals. In Figure 2(c), 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(c) 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.

(a) Outside image of the car

(b) Driver's facial image



(c) Operation signals

Figure 2. Example of driving data measured during the experiment 8, where (a) shows the outside image, (b) shows the driver's facial image and (c) shows the driver's operation signals

4. Driver Model Based on Nonlinear Autoregressive Exogenous Input (NARX) Model.

4.1. **Sensitive analysis of the operation signals.** 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 3 shows the calculation results, where the top figure denotes the average values of the vehicle speed, the middle figure denotes the average values of the synthetic pedal pressure and the bottom figure 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 have 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.

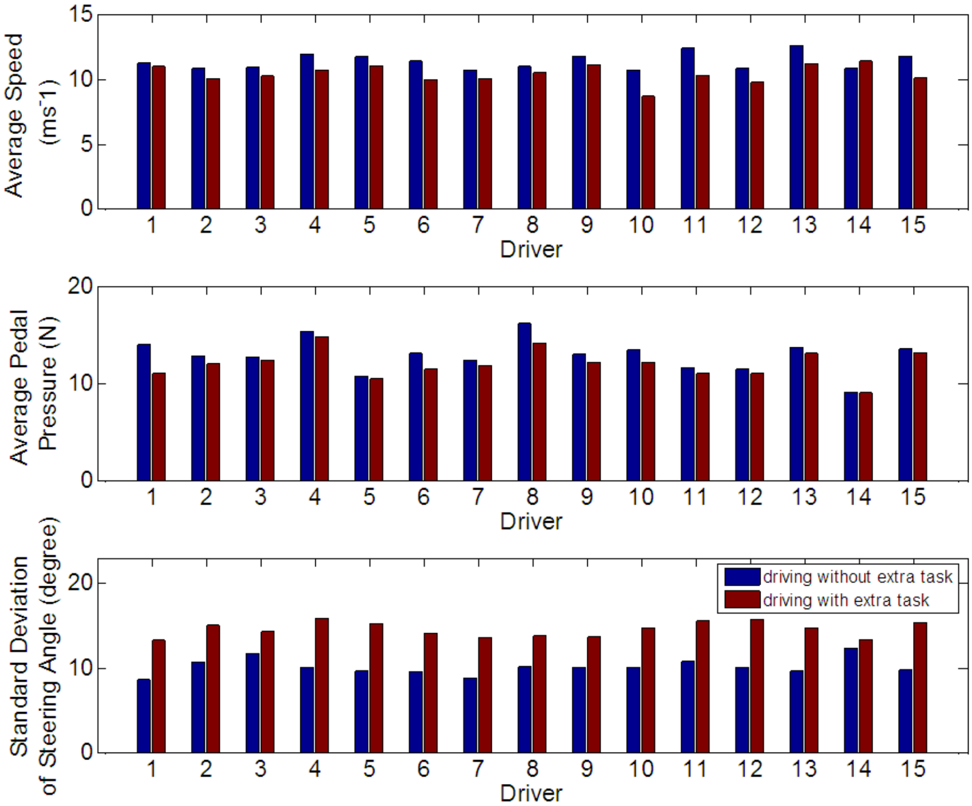


FIGURE 3. The effect of the secondary tasks to the driver performance

4.2. **Driver model structure.** 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:

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

where $u(t)$ and $y(t)$ are the model inputs, $\hat{y}(t)$ is the estimated model output, $n+1$ is the number of inputs and k is the model time delay. In this study, there are three input signals ($n+1=3$), 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 [23], 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 shows the structure of the NARX network used in this study.

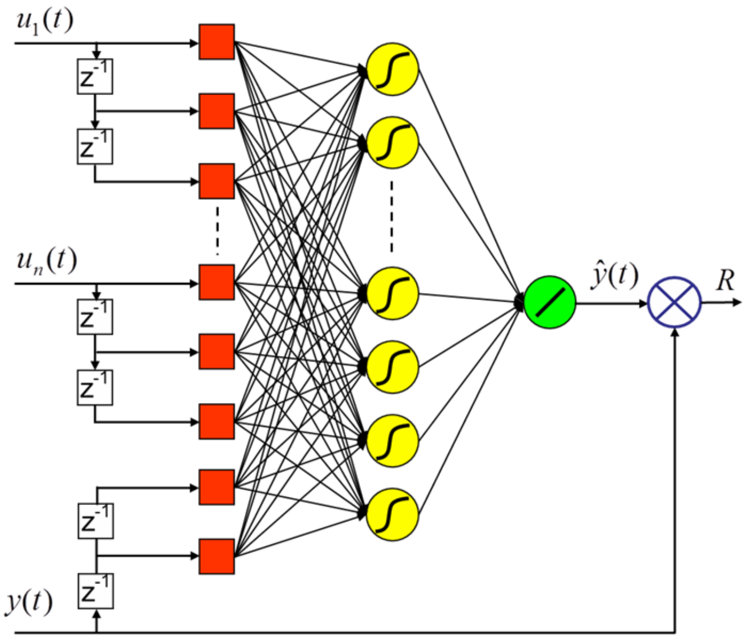


FIGURE 4. The structure of the NARX network

The NARX network performs its calculations such that the output of the jth neuron in the middle layer is expressed as Equation (2):

$$h_j = g_j \left[\sum_{i=1}^{n} (w_{ji} u_i + b_j) \right], \quad i = 1, \ldots, n, \ j = 1, \ldots, n_j \tag{2}$$

where $u_i(t)$ is the ith network input, w_{ji} is the connection weight from the ith neuron in the input layer to the jth neuron in the middle layer, b_j is the weight from the bias to the jth 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):

$$\hat{y}_o = g_o \left[\sum_{j=1}^{n_j} (w_{oj} h_j + b_o) \right], \quad j = 1, \ldots, n_j, \ o = 1 \tag{3}$$

where w_{oj} is the weight connecting the jth 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 Hessian matrix, the Levenberg-Marquardt algorithm [24], 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 (4) is minimize.

$$E(\vec{w}) = \sum_{l=1}^{k} e_l^2(\vec{w}) = ||f(\vec{w})||^2 \tag{4}$$

where $e_l(\vec{w}) = x_l - \hat{x}_l(\vec{w})$, x_l is the target value and $\hat{x}_l(\vec{w})$ 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:

$$\vec{w}_{m+1} = \vec{w}_m + \delta\vec{w}_m \tag{5a}$$

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

$$\delta\vec{w}_m = \frac{-(J_m^T f(\vec{w}_m))}{(J_m^T J_m + \lambda I)} \tag{5b}$$

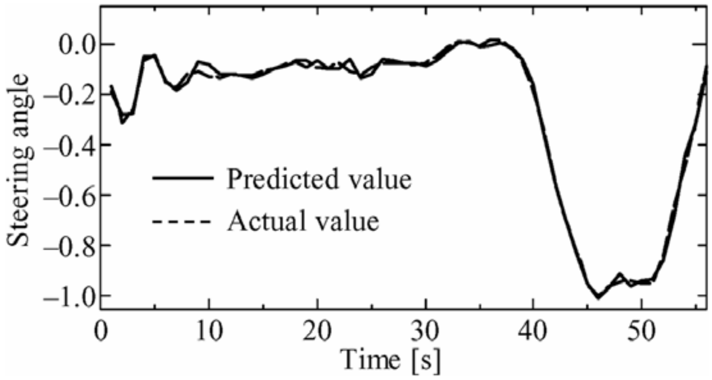
In Equation (5b), J_m is the Jacobian of $f(\cdot)$ evaluated at $\vec{w}_m$, λ is the Marquardt parameter and I is the identity matrix [25]. In summary, the learning algorithm used to train driver model in the form of NARX network can be summarized as follows:

(i) Calculate $E(\vec{w}_m)$ by using Equation (4),
(ii) Begin with a small value of λ, e.g., $\lambda = 0.01$,
(iii) Solve (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).

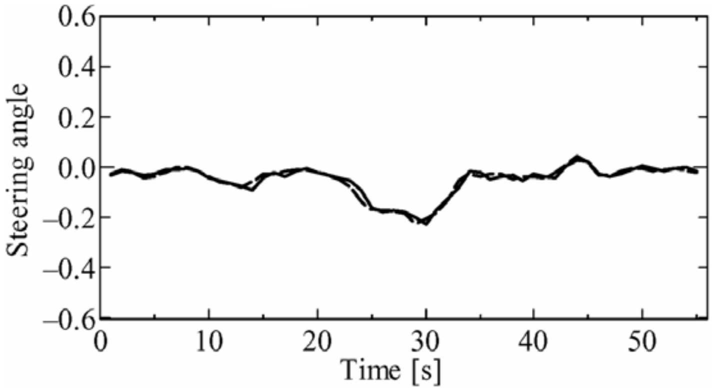
4.3. **Model fitting and validation.** The operation signals of neutral driving from experiment 8 without the secondary task were used for model fitting for each driver. Model fitting was carried out by the learning process described in Section 4.2. The model was then validated using the operation signals 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 5 shows 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 and (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 5. 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.

5. **Inattention Analysis.** 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



(a) Fitting result



(b) Validation result

FIGURE 5. Example of the actual signals and predicted values of driver action, where (a) shows the fitting result and (b) the validation result

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 for driving with a secondary task, the standard deviation increases.

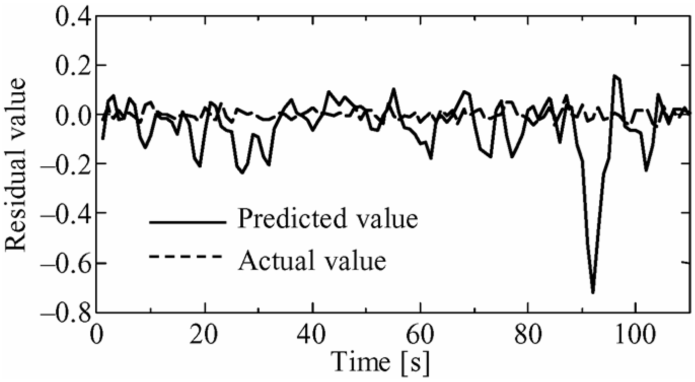
5.1. **Inattention analysis using driver model.** In this study, operation signals from experiment 9 were used as the inattentive driving data to test the model. In experiment 9, each driver is instructed to loudly repeat four randomized alphanumeric letters that are given through the driver's earphone. 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 6 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.

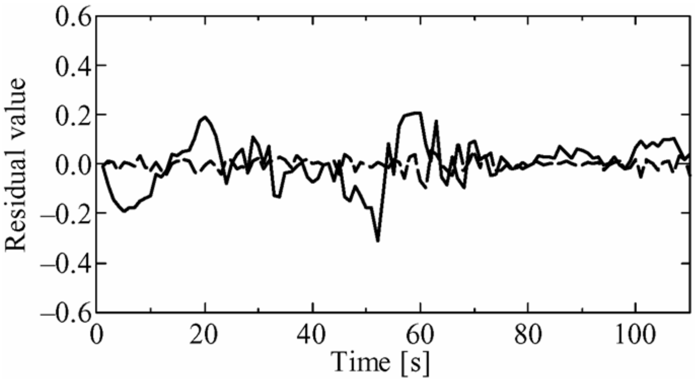
5.2. **Evaluation of analysis results.** The performance of the model was analyzed by studying the model residuals, i.e., the differences between the actual operation signal and model-predicted driver actions. Furthermore, the root mean square (RMS) value of the model residual was calculated using Equation (6) in order to confirm the model performance.

$$RMS = \sqrt{\frac{1}{s}\sum_{r=1}^{s}(e_r)^2} \tag{6}$$

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.



(a) Residual value of driver 1



(b) Residual value of driver 14

FIGURE 6. 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

Figure 7 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 7, in the case of neutral driving, the *RMS* values for fitting and validation are very small for all 15 drivers, which also indicates the effectiveness of the model. That is, the model can almost predict the output actual 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 (7).

$$C = 100e^{-R_{rms}}\ [\%] \tag{7}$$

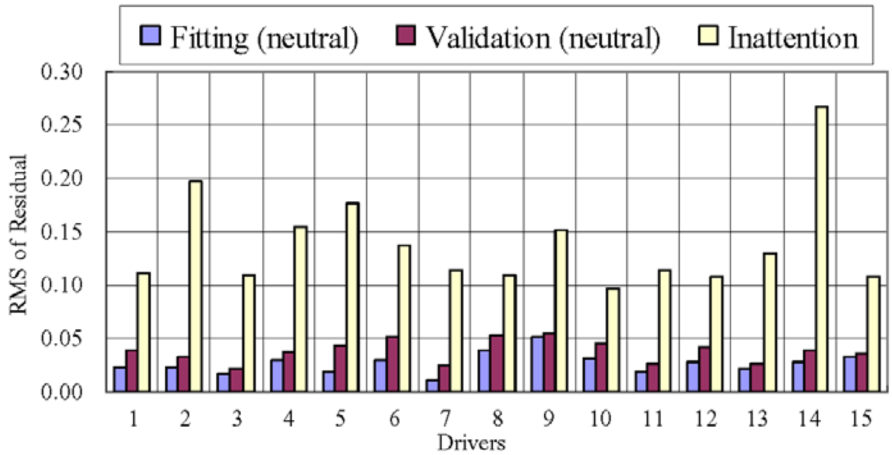


FIGURE 7. *RMS* values of the neutral driving (fitting and validation process) and the inattention driving for all drivers

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 (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 8 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.

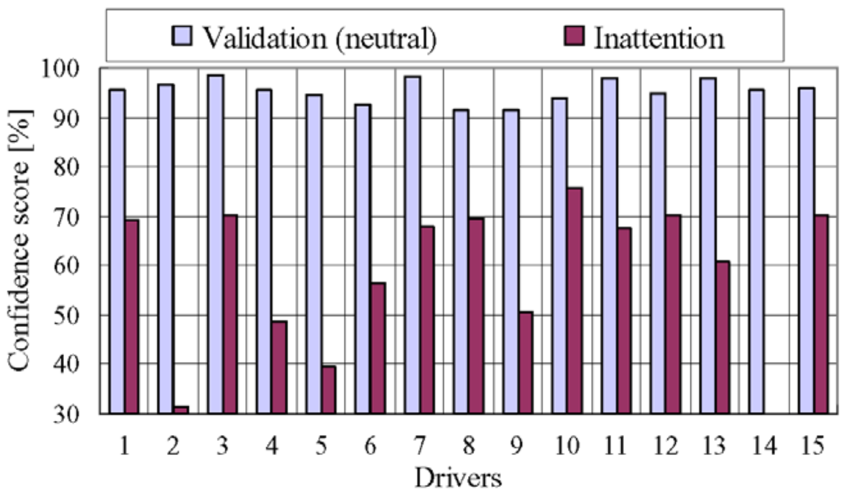


FIGURE 8. The percentage of confidence score from fitting, validation, testing and inattention driving data for the all drivers

6. **Conclusion and Future Work.** This paper 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.

Future work can seek to determine which secondary tasks give the highest effect on driver inattention. Additionally, we intend to examine the influence of the secondary task for inattentive driving in different conditions of driving experience, driver's behavior and investigate new informative features from model residuals and develop a system to evaluate driver inattention.

Acknowledgement. A part of this research was supported by: the Global COE program "Frontier of Intelligent Sensing", Toyohashi University of Technology and Ministry of Education, Culture, Sport, Science and Technology (MEXT), JAPAN. The authors also gratefully acknowledge the supply of driving data, which was collected by Takeda Laboratory, Nagoya University.

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