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Dual Particle Filtering of Intelligent Driver Model Parameters for Indirect Detection of Driving Anomalies

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ABSTRACT

Abnormal driving behavior, such as excessive speed and reckless and aggressive driving, is recognized as causing more than 50% of fatal accidents. The detection of abnormal driving behavior has a wide range of applications and is expected to be used not only to directly suppress abnormal driving behavior but also to be factored into the price of automobile insurance premiums. This paper proposes a new approach to abnormal driving detection that requires neither in-car cameras nor physiological sensors. Instead, this approach makes full use of an intelligent driver model (IDM) and its parameters, where vehicle acceleration is assumed to indicate abnormal driving behavior. In an experiment using a driving simulator, subjects were asked to text on a mobile phone to collect data on their driving behavior with and without distractions. Numerical analysis showed that IDM parameters estimated by dual particle filtering could accurately detect driving abnormalities without the use of direct driver monitoring systems such as on-board cameras or sensors.

Keywords: Driving anomaly, Anomaly detection, Intelligent driver model, Particle filter, State estimation

INTRODUCTION

Abnormal driving behavior, such as excessive speed and reckless and aggressive driving, are recognized as the cause of more than 50% of fatal accidents (AAA Foundation of Traffic safety, 2009). Laws regulating these behaviors have proven to be effective to a certain extent in reducing abnormal driving behavior. However, it remains difficult to detect latent abnormal driving behavior that even the drivers themselves are unaware of (Ucar et al., 2021). The detection of abnormal driving behavior has a wide range of applications and is expected to be used not only to directly suppress abnormal driving behavior but also to help set automobile insurance premiums (Zhang et al., 2017).

Most current driver monitoring systems can be applied to the detection of abnormal driving, but most of them require either in-car cameras for face, eye, and head motion recognition or the use of sensors to evaluate vehicle movement (Kashevnik et al., 2021). However, the accuracy of driver monitoring cameras can be degraded by the driver's eyeglasses or a mask.

For detecting abnormal driving behavior, methods for scoring aggressive driving behavior by linear regression based on vehicle states such as acceleration and speed (Li et al., 2015), modelling abnormal states using graph theory (Zhang et al., 2017), determining aggressive driving behavior by machine learning (Matousek et al., 2019), and evaluating abnormal driving behavior by deviation of vehicle states from reference values (Ucar et al., 2021) have also been reported. However, because acceleration and speed data contain a variety of factors, it is difficult to detect abnormal driver behavior from these data alone. In addition, machine learning requires a large amount of training data for parameter identification, so the accuracy of the detection model is highly dependent on the amount of data collected.

This paper proposes a new approach to abnormal driving detection that does not require in-car cameras, physiological sensors, or machine learning. Instead, this approach makes full use of an intelligent driver model (IDM) and focuses on its parameters, with the assumption that abnormal driving behavior is reflected in vehicle acceleration. The acceleration alone is insufficient for driving anomaly detection, but the IDM parameters estimated from the acceleration should contain valuable information related to the driver's attention state, intention, and sensitivity. Driving simulator experiments were conducted with and without driver distractions, and the performance of the proposed method was evaluated to see if abnormal driving due to distraction could be detected with high accuracy.

METHODOLOGY

IDM

The IDM used in this study is a family of social force models that encourage drivers to travel at safe speeds and maintain appropriate vehicle distances so as not to cause rear-end collisions (Kesting et al., 2007). Note here that the IDM is a collision-free model. The formula of the IDM is given by

$$a_i(k) = a\left[1-\left(\frac{v_i(k)}{V}\right)^4-\left(\frac{D(k)}{d_i(k)}\right)^2\right], \tag{1}$$

$$D(k) = s+v_i(k)\cdot T-\frac{v_i(k)\left(v_{i-1}(k)-v_i(k)\right)}{2\sqrt{ab}}, \tag{2}$$

where a (maximum acceleration), b (comfortable deceleration), V (desired velocity), T (desired safe time headway), and s (minimum stopping distance) are the model parameters and $a_i\,(k)$, $v_i\,(k)$, and $d_i\,(k)$ are the acceleration, relative velocity, and headway distance of vehicle i at time k. Vehicle "$i-1$" is the preceding vehicle. The five parameters of the IDM contain valuable information on driver characteristics, including anomalies. These parameters change in real time in response to the environment, in particular the movement of the preceding vehicle. Online estimation of parameters can accurately identify the characteristics of the driver at any given moment (e.g., 0.1 s).

Parameter Estimation by a Dual Particle Filter (DPF)

The proposed approach requires online estimation of IDM parameters using a dual particle filter (DPF), which is recognized as one of the most powerful tools for state estimation (Haykin, 2001). The state–space model of the particle filter is given by

$$\boldsymbol{\theta}_k = \boldsymbol{\theta}_{k-1} + \mathbf{r}_{k-1} \text{ and } \mathbf{y}_k = \mathbf{g}\left(\boldsymbol{\theta}_{k-1}, \mathbf{x}_{k-T}\right) + \mathbf{n}_k \tag{3}$$

where $\mathbf{y}_k = a_i(k)$ and $\mathbf{x}_k = [d_i(k), v_i(k), \text{and } v_{i\text{-}1}(k)]^T$ are the measurement and input vectors, respectively, and $\mathbf{r}_k$ and $\mathbf{n}_k$ are the system and measurement noise vectors, respectively. The nonlinear function $\mathbf{g}$ is the IDM itself given by Equations (1) and (2).

In the DPF, as shown in Figure 1, the parameter vector is separated into five parameters a, b, V, s, and T and for each parameter, a separate particle filter is provided, such as PF_a for a and PF_T for T. As an example, the procedure for PF_a is shown in Table 1. The updated a is fed into PF_b for b estimation, and this process is repeated through PF_T, after which all five variables are fed back into PF_a with time update $k=k+1$.

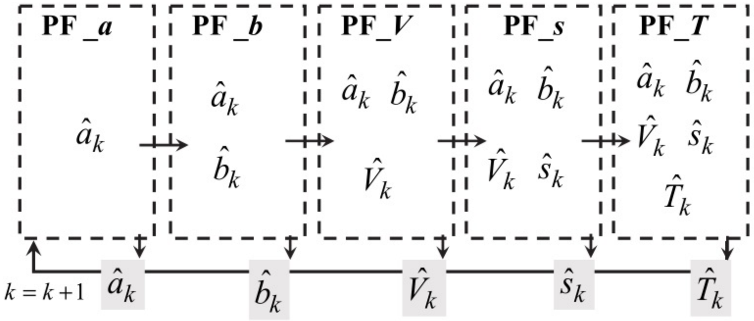

Figure 1: Procedure of dual particle filter.

Table 1. Procedure of general particle filter for parameter "a".

Generation	$\tilde{a}_k^{(j)} = \hat{a}_{k-1}^{(j)} + r_{a,k}$
Prediction	$\tilde{y}_k^{(j)} = g\left(\tilde{a}_k^{(j)}, b_{k-1}, V_{k-1}, s_{k-1}, T_{k-1}, x_{k-1}\right) + n_k$
Weight	$\tilde{w}_k^{(j)} = N\left(\mathbf{y}_k - \tilde{\mathbf{y}}_k^{(j)}, \mathbf{n}_k\right)$
Resampling	$\hat{a}_k^{(j)} \sim \begin{cases} \tilde{a}_k^{(j)} \text{ with prob. } \tilde{w}_k^{(1)} \\ \tilde{a}_k^{(j)} \text{ with prob. } \tilde{w}_k^{(2)} \\ \vdots \\ \tilde{a}_k^{(j)} \text{ with prob. } \tilde{w}_k^{(M)} \end{cases}$
Update	$\hat{a}_k = \frac{1}{M}\sum_{j=1}^{M} \hat{a}_k^{(j)} = \sum_{j=1}^{M} \tilde{w}_k^{(j)} \tilde{a}_k^{(j)}$

Algorithm for Detecting Driving Anomalies

Punzo et al., (2014) concluded that estimating only two of the five parameters is sufficient. The rest are treated as constants. This is called a partial model, whereas in the full model, all five parameters are estimated. We focused on the partial model when developing the algorithm for detecting driving anomalies.

In our experience, the full model perfectly reproduces the driver's acceleration in any situation, as the combination of the five parameters is accurately estimated by the DPF. However, if the partial model fails to reproduce the acceleration, this means that there were anomalies in driving such that the constant three parameters could not reproduce the driver's acceleration. The deviation between the reproduced and actual acceleration can therefore be treated as the magnitude of a driving anomaly.

Figure 2 shows an example of the algorithm for detecting abnormal driving. The orange curve is the actual acceleration, whereas the blue one is the acceleration reproduced by the IDM. At time (A), the driver should have decelerated by –5.5 m/s^2 to avoid a collision but failed to decelerate sufficiently and only decelerated by –0.5 m/s^2. This deviation can be treated as the severity of a driving anomaly. If there are no anomalies, even the partial model can completely reproduce the driver's acceleration as accurately as the full model.

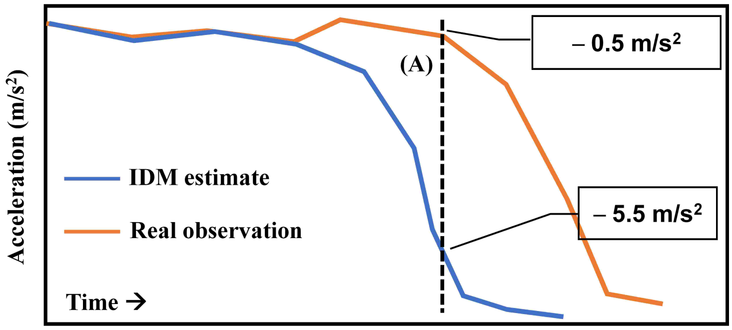

Figure 2: Example of the algorithm for detecting a driving abnormality.

NUMERICAL ANALYSIS

Driving Simulator Experiment

The evaluation data used in this study were obtained through a driving simulator experiment approved by the Ethics Committee of the Nippon Institute of Technology. In these experiments, seven participants (referred to as subjects 1 to 7) were asked to travel along a straight road 3.5 km long by following another vehicle with a shorter distance than usual. The speed of the preceding vehicle varied from 0 to 20 m/s during the 5-min simulations. In the experiment, the participant was supposed to encounter sudden deceleration of the preceding vehicle five times between –0.2 G and –0.5 G. The primary task was to follow the vehicle ahead and avoid a collision, while the secondary task was to enter text on a smartphone. After providing informed consent, seven drivers (mean age and standard deviation of 21.6 and 0.610, respectively) agreed to participate in these experiments.

DPF Setup

For the dynamic estimation of IDM parameters, the covariance of system noise was set to 0.1–0.5 and the measurement noise to 0.3. The number of particles was set at 500. The parameters were estimated every 0.1 s.

Distraction Detection by Partial Model

Figure 3 compares acceleration by the full and partial models of subject 2 with distraction. The full model fully reproduces the driver's acceleration for the entire period, except for a rear-end collision at around time 800. This shows that the IDM performs very well and that the DPF shows an excellent ability to describe the driver's acceleration behavior.

However, there are deviations between the IDM and the actual acceleration where the partial model failed to reproduce the acceleration, especially when the driver decelerated. It is obvious that this deviation was caused by driver distraction. This means that there was abnormal driving such that the three constant parameters of the partial model could not reproduce the acceleration.

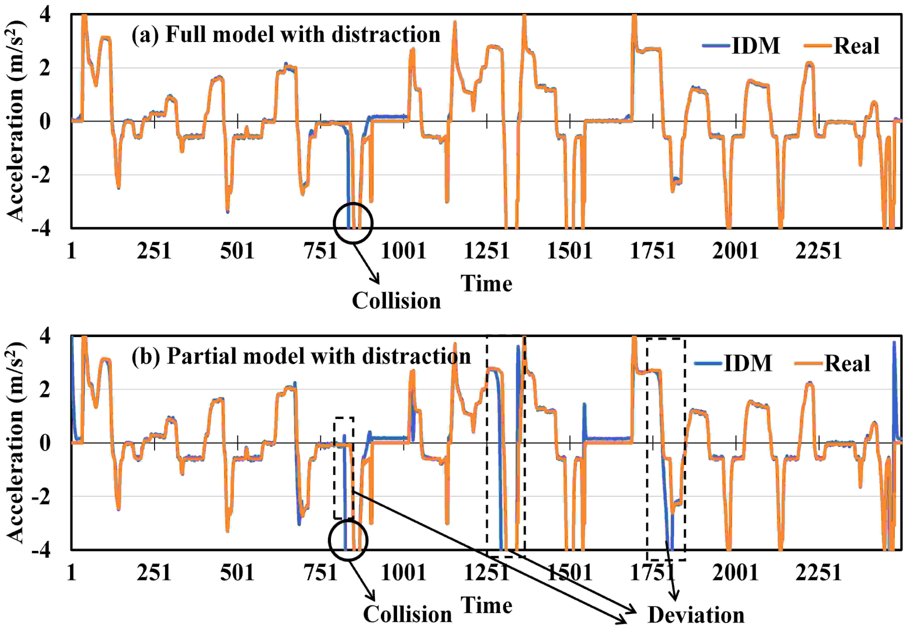

Figure 3: Comparison of full and partial models of subject 2 with distraction. The full model (top) reproduced acceleration perfectly, while the partial model (bottom) failed to accurately depict deceleration on several occasions due to driver distraction.

Another example is subject 1 with distraction shown in Figure 4. Both the full and partial models reproduced the accelerations very accurately, except for a slight deviation around time 1751. In other words, the driving of subject

1 did not have an anomaly, even when the subject performed the secondary task of using the smartphone. Clearly, even in distracted situations, it is difficult to identify whether the driver is focused on the primary task. However, it is obvious that the driving of subject 2, who encountered a collision, is more abnormal, hazardous, and distracted than that of subject 1.

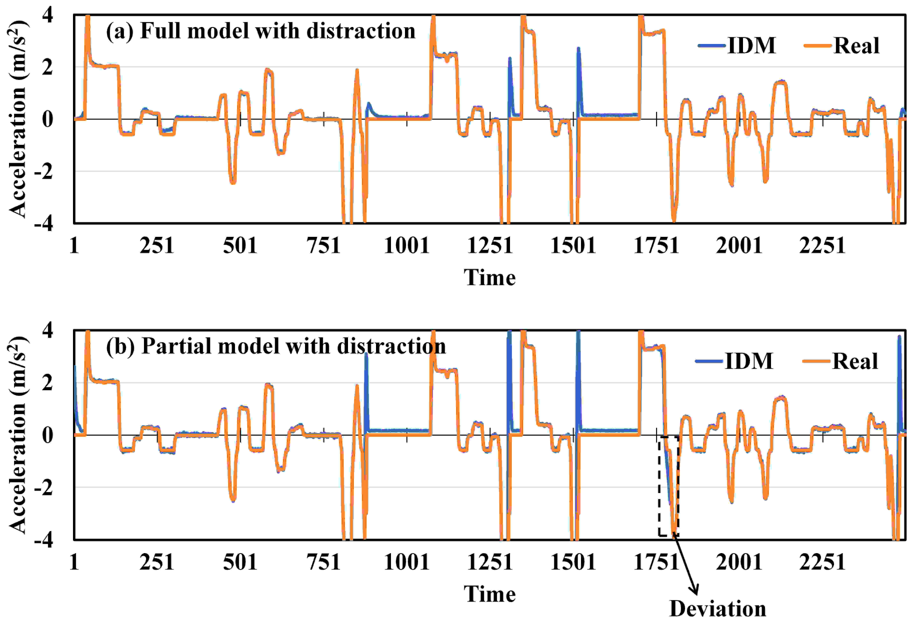

Figure 4: Comparison of full and partial models of subject 1 with distraction. Both the full and partial models reproduced the accelerations very accurately, except for a slight deviation around time 1751.

As shown by the comparison of the full and partial models, our proposed approach has the potential to detect driving abnormalities without the use of in-car cameras for face and eye recognition or head motion detection. As a next step, it was necessary to examine whether the deviations in acceleration in the partial model are due to driver distraction rather than simple estimation error. For this purpose, it was necessary to compare the case with and without distraction.

Figure 5 compares the acceleration obtained by the partial model with and without distraction (subject 2). The distraction scenario (bottom) causes deviations, while the no-distraction case (top) reproduces the acceleration perfectly, even in the case of rapid deceleration. In normal driving, where the driver pays attention to the vehicle ahead, the partial model can fully describe the driver's acceleration. This means that the IDM using the estimated parameters is complete and no estimation errors occur. However, once the driver becomes distracted, the partial model with three constant parameters cannot describe such abnormal driving, and the effect of the distraction is reflected in the deviation between the reproduced and actual accelerations.

The deviation is therefore not due to errors in the model, but rather to driver distraction.

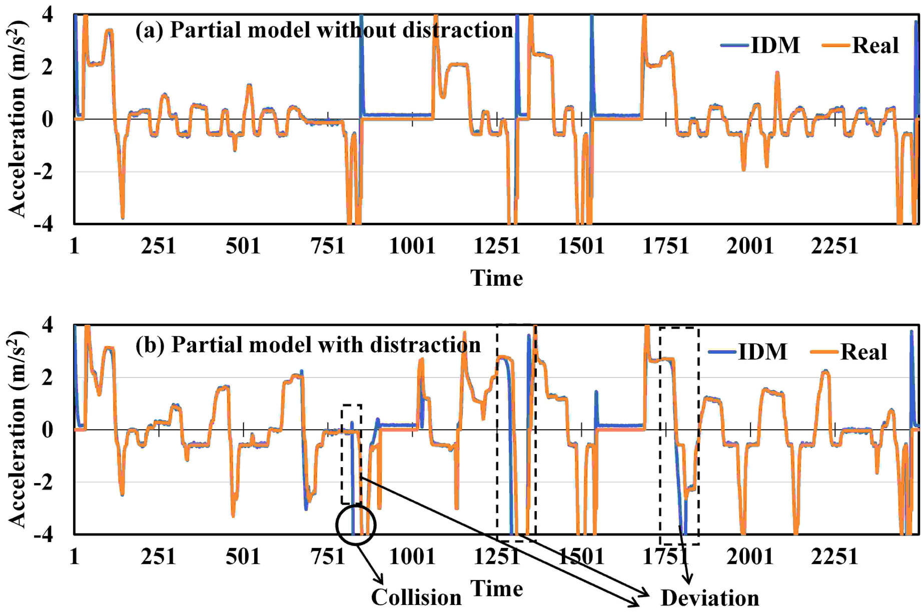

Figure 5: Comparison of acceleration by partial models with and without distraction (subject 2). In the absence of distraction (top), the partial model perfectly reproduces the acceleration, but in the distraction scenario (bottom), the partial model can no longer describe such abnormal driving, resulting in deviations, especially in deceleration situations.

CONCLUSION

This study evaluated an IDM estimated by the DPF and used the IDM parameters to detect driving anomalies. This is a new approach that requires neither in-car cameras nor physiological sensors for driver monitoring. Specifically, abnormal driving is identified indirectly using vehicle controller area network (CAN) data and mathematical models.

A driving simulation experiment was carried out, in which seven participants were asked to drive down a straight corridor with and without distractions. Numerical results show that a partial model in which three IDM parameters that are assumed to be constant can detect anomalies with high accuracy and sensitivity. The ability to detect abnormal driving using only the vehicle's CAN data, without the use of on-board cameras, is a major advantage of our proposed approach. Further development is needed to compare the proposed approach with conventional methods.

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