

Investigation of Inattentive Driving Estimation Method by Using Longitudinal and Lateral Driver Operational Models

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ABSTRACT

Recently, a number of researches on detecting such inattentive driving have been carried out, and various detection methods have been proposed. In this paper, using driving data which can be measured with existing on-board vehicle sensors, the authors focus on headway distance behavior which relates to rear-end collision as well as the steering behavior which can be used to detect driver drowsiness. The emphasis of this study is that the inattentive driving can be potentially detected from the driving behavior deviated from the normative characteristics considering the transfer function from the environment to the driving operation. Therefore, intrusive measurement methods such as physiological measurement are not required. In addition, to detect the inattentive state by the criterion of the individual driver, the driver assistance system can be realized in the way that it can be adapted not only to various types of drivers, but also to the driver real-time driving state. In this study, the driver models are employed to estimate the normative driving. The driver models in car-following and in lane-keeping situations are constructed independently, and basically the constructed models are assumed to be the general dynamical system models. The driving data in the normative driving and in the inattentive driving were compared with these reference driver models. According to analysis results, this study exhibits the feasibility of the proposed method that it can detect the inattentive driving level by using the reference driver models.

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INTRODUCTION

According to the ITARDA-report [1], most of rear-end accidents are caused by carelessness with preceding vehicle such as inattention, drowsiness or unconsciousness. Recently, a number of researches on detecting such inattentive driving have been carried out, and various detection methods such as using physiological information (e.g. heart rate) or using vehicle dynamics information (e.g. steering behavior) have been proposed[2][3]. Here, the authors focus on headway distance behavior which relates to rear-end collision, the inattentive driving estimation was successful by using the distribution of deviation from the reference driver model based on only headway distance and vehicle velocity which can be measured with existing on-board vehicle sensors[4]. Figure 1 shows the individual adaptation algorithm. First, the individual characteristics such as naturalistic headway distance are extracted from the driving data of driver, vehicle and environment collected by using a continuous logging drive recorder. Next, the deviated states such as the low attention and the inattentive performance for following task

are detected by comparing the current driving data with the driver model relevant to the longitudinal and the lateral vehicle dynamics based on the extracted characteristics. Finally, the system assists the driver depending on the degree of the driving state degradation. The information of driver state can be utilized to determine the appropriate way to assist the drivers such as the information guidance, driving advisory, collision warning or intervention operation, in order to improve the driver acceptance of the system.

Figure 2 shows the conceptual diagram of a model-based method estimating driver state based on the adaptive control theory corresponding with Figure 1. First, it is assumed that the driver operates steering wheel and pedals based on recognition of driving lane and behavior of preceding vehicle. Then the vehicle responds according to the operation from the driver. This process is treated as a plant and the system which has the same function as the plant are constructed as driver and vehicle models. In particular, the driver models are always supposed to estimate the normative driving in every driving environment. And then, the outputs from the vehicle models whose inputs are from the driver models are obtained.

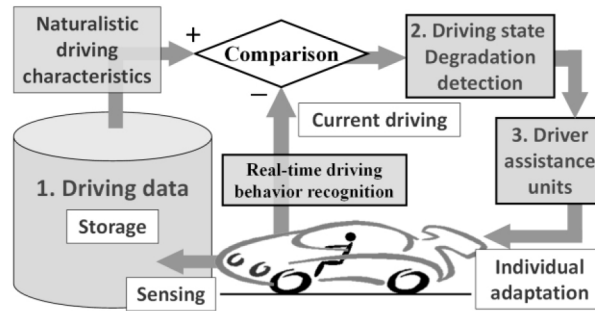


Figure 1. Individual adaptation algorithm

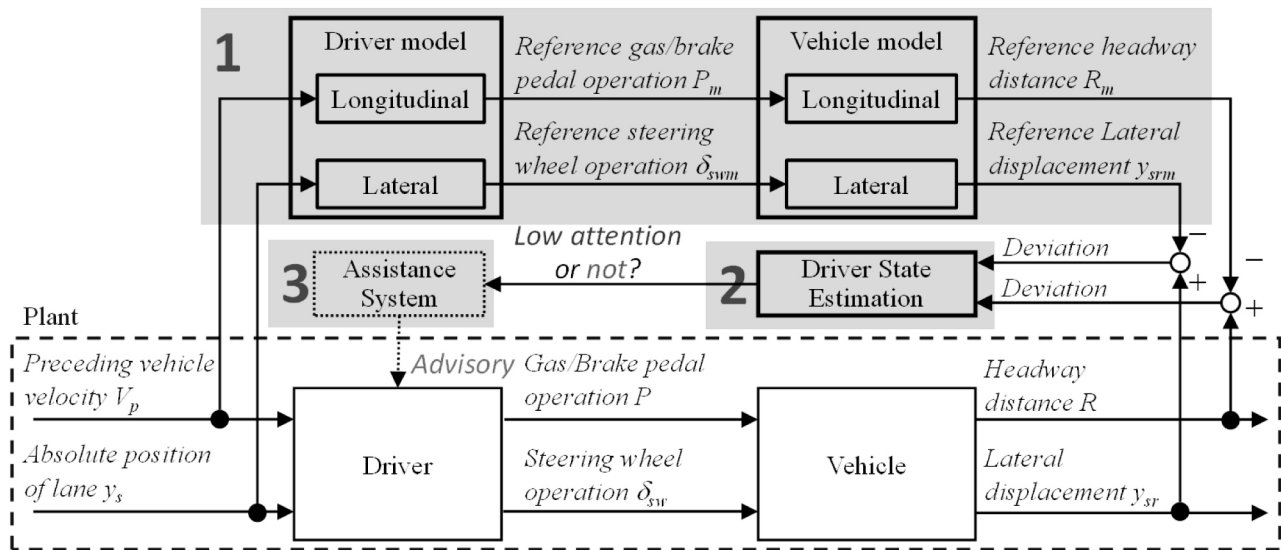


Figure 2. Model-based driver state estimation

Comparing the outputs as the reference driving to the measured driving data, the driving state can be estimated by using error between them. The result of driver state estimation will be possible to utilize in driving assistance system which prevents the driver from an accident caused by the inattentive driving.

This study proposes the detecting method using the car-following performance as well as the lane-keeping performance. This paper describes the model-based inattention driving estimation method by using the on-vehicle sensor data such as the headway distance, the velocity and the lateral deviation from the center of the lane.

DRIVER-VEHICLE MODEL

The vehicle-control driver models in the form of input-output relationship are employed to express the normative driving. In this study, the driver models in the car-following and the lane-keeping situations are constructed independently, and basically the constructed models are assumed to be the general dynamical system models. In addition, the driver state estimation by using these models is also carried out independently so that the driver state can be

estimated by using only lateral driver model when there is no preceding vehicle. These models do not take into the account the road inclination, the width of road, the number of lanes and the weather condition.

Car-Following Driver Model

First, this study proposes the reference driver model based on assumption that the driver maintains a safe distance between a preceding vehicle and the host vehicle. In this model, both vehicles are connected with a virtual spring and a virtual damper as shown in the pictorial diagram in Figure 3. This model is simple, but it is utilized as the algorithm for autonomous platoon driving[5], and it will be possible to estimate the individual adaptive driving behavior by tuning the parameter in this model. The equation of motion of this model is expressed as Eq. (1).

$$\begin{aligned} a_m^*(t) &= H_R(R_m(t) - R^*(t)) + H_V(V_p(t) - V_m(t)) \\ \therefore H_R &= k/m, H_V = c/m, R^*(t) = T_{hw}^* \cdot V_m(t) \end{aligned} \quad (1)$$

where, a_m^* denotes the desired longitudinal acceleration of the driver, R_m denotes the headway distance as the output

from the model, R^* denotes the objective headway distance varied among individual drivers and it has a linear-approximation relationship with the host vehicle velocity, T_{hw}^* denotes the gradient of it, V_p denotes the preceding vehicle velocity, V_m denotes the host vehicle velocity as the output from the model, H_R and H_V denote the dynamic parameters which are assumed to be time-variant values depending on the driving condition, k denotes the virtual spring constant, m denotes the vehicle mass and c denotes the virtual damper damping coefficient. The subscript m refers to the value from the reference model. Eq. (2) indicates the pedal operational logic.

$$G_p(s) = \begin{cases} G_{pgs}^{-1}(ma_m^* - F_d)e^{-\tau s} & \because a_m^* \geq F_d/m \\ G_{pbp}^{-1}(-ma_m^* + F_d)e^{-\tau s} & \because a_m^* < F_d/m \end{cases} \quad (2)$$

where G_p denotes the pedal operational gain of the driver, G_{pgs}^{-1} denotes the inverse of the transfer function for gas pedal control, G_{pbp}^{-1} denotes the inverse of the transfer function for brake pedal control, F_d denotes the drag forces acting on the vehicle and τ denotes the driver's time delay. To simplify the driver model, based on the assumption that there is no sudden acceleration or deceleration during steady car-following situation, the longitudinal vehicle dynamic characteristics can be neglected. Therefore, the intended acceleration by the driver becomes equal to the actual acceleration as shown in Eq.(3).

$$a_m(t) = H_R(R_m(t) - R^*(t)) + H_V(V_p(t) - V_m(t)) \quad (3)$$

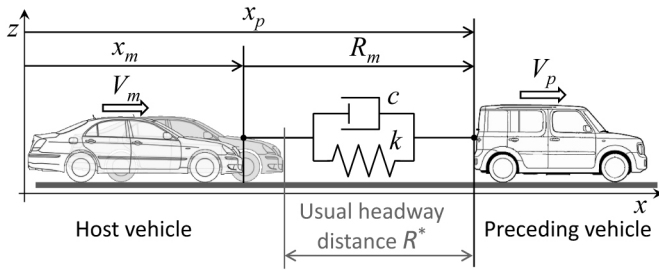


Figure 3. Car-following driver model

Lane-Keeping Driver Model

On the other hand, in the lane-keeping state, this study proposes the preview model as the reference model shown in Figure 4. This model is generally used in the autonomous lane keeping control algorithm[6]. The equation of this model is expressed as Eq.(4).

$$\begin{aligned} \delta_{swm}(t) &= h(y_{srm}(t) - y_0) \\ &= h\{(y_s^*(t) - y_0) - (y_{cm}(t) + T_p \cdot V(t) \cdot \psi_m(t))\} \end{aligned} \quad (4)$$

where, δ_{swm} denotes the steering wheel angle, h denotes the driver compensation gain, y_{srm} denotes the lateral deviation

from the road center to the preview point, y_s^* denotes the absolute position of the road center, y_{cm} denotes the absolute lateral position of the vehicle, T_p denotes the preview time and ψ_m denotes the yaw angle with regard to the desired path. The lateral vehicle model is based on an equivalent two-wheel vehicle model, one of typical vehicle model governing the lateral motion and the yaw motion.

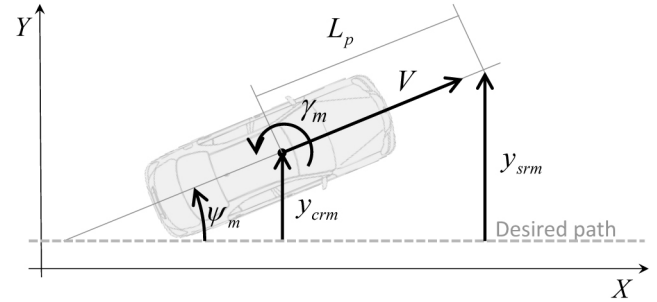


Figure 4. Description of variables in lane-keeping driver model

DATA COLLECTION

Experimental Equipment

The long-term real world driving data was collected by using the experimental car equipped with the continuous logging drive recorder which consists of the information of road environment (GPS data and headway distance), driver operation (steering, pedal, winker), and vehicle dynamics data (speed, acceleration, yaw rate, etc.). The six video images of front scenery, rear scenery, driver's face and driver's foot motion in pedal operation are captured in synchronization with the sensor data. The configuration of the continuous logging drive recorder is shown in Figure 5.

The absolute position of the road center y_s^* which is used to the lane-keeping driver model cannot be logged directly from the CAN, so it is required to get the lateral deviation by detecting the lane position. The flow of the lane detection algorithm is shown in Figure 6.

First, the Canny's algorithm is used to extract boundaries of the white lines on a road. Next, the white lines are detected. The bright pixels are searched from the image which is applied the Canny's filter, and a set of successive bright pixels is assumed as a line segment. It is decided that the line segment whose length is the longest in candidates of the line segments which are the biggest slopes. Finally, the locations of the white lines in real-world are calculated from the position of them on the image. The locations of the white lines on both sides at 5~30 meters from the front of the host vehicle are gotten by associating the pixel coordinate on the image with the space coordinate in real-world in advance. The lane width on expressway in Japan is determined as 3.5 meters, so it is able to correct the pitch effect by using this determination. The absolute position of the road center y_s^*