

A Study on Modeling of Driver's Braking Action to Avoid Rear-End Collision with Time Delay Neural Network

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ABSTRACT

Collision avoidance systems for rear-end collisions have been researched and developed. It is necessary to activate collision warnings and automatic braking systems with appropriate timing determined by a monitoring system of a driver's braking action. Although there are various systems to monitor driving behavior, this study aims to create a monitoring system using a driver model. This study was intended to construct a model of a driver's braking action with the Time Delay Neural Network (TDNN).

An experimental scenario focuses on rear-end collisions on a highway, such as the driver of a host vehicle controlling the brake to avoid a collision into a leading vehicle in a stationary condition caused by a traffic jam. In order to examine the accuracy of the TDNN model, this study used four parameters: the number of learning, the number of neurons in the hidden layer, the sampling time with 0.01 second as a minimum value, and the number of the delay time. In addition, this study made a comparative review of the TDNN model and the Neural Network (NN) model to examine the accuracy of the TDNN model.

It was found that (1) TDNN allows for establishing a model with higher repeatability of a driver's driving action, (2) when comparing with NN, the accuracy of the model was improved for TDNN, and (3) even if a driver repeatedly presses the brake pedal in a short time, TDNN can accurately simulate a complex braking action by a driver.

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INTRODUCTION

Humans have a great variety of characteristics, and express their individual personalities. Such personalities are also expressed while they are driving vehicles, and each automobile in certain traffic conditions has a subtle difference in their motion. For example, a passenger in a vehicle may feel uncomfortable if the driver is driving with an excessively short headway distance from the leading vehicle, or braking late. In such a case, the passengers in vehicles may not feel at ease, even if they are safe and do not collide with a leading vehicle. In particular, braking actions differ greatly in timing between individuals, with each one using a wide variety of characteristics to start braking and to press the brake pedal. A passenger would incur a great mental burden of discomfort or nuisance, if braking actions by a driver differ from the passenger's style in timing and braking force. In recent years,

driving assist systems have been developed so that they give drivers a warning before a collision, and automatically activate brakes to avoid collisions or mitigate damage from collisions by detecting the distance from a leading vehicle with a sensor. Although these systems are required to be activated at an appropriate timing in order to avoid a collision accident, activation of warnings that occur too early or the activation of automatically commanded braking would cause a driver to feel discomfort or nuisance, which may lead the driver to turning off the system's functions. From the standpoint of accident prevention, efforts to formulate regulations for the systems designed for collision avoidance and collision damage mitigation are underway worldwide. For example, the working party (WP. 29) of the United Nations Economic Commission for Europe has adopted the Advanced Emergency Braking System (AEBS) for commercial vehicles for Regulation No. 131 to

which European nations and Japan accede, while NHTSA (National Highway Traffic Safety Administration) in the United States has studied the standards for Crash Imminent Braking (CIB) [1][2]. In implementation of these regulations, such as AEBS and CIB, the selection of effective scenarios was based on the current accident data, where the number of prevented accidents were calculated, and then the details to be included in the regulations were prepared. While these regulations are expected to be effective to a certain extent reducing in collision accidents, collision accidents actually have a variety of patterns. Thus, the realization of accident prevention in various scenarios will be expected in the future. Accordingly, as a method to further enhance the effectiveness of accident prevention in the future, this study envisions that a driver would be monitored whether they take an appropriate braking action, and based on the result of that monitoring, the collision avoidance system would be activated at the appropriate time [3]. Though various methods are available to monitor a driver's driving behavior, this study aims at building a driver model for monitoring driving actions, comparing a driver's driving behavior with such a model. [4][5] Therefore, this study first targets drivers' braking actions for building its model.

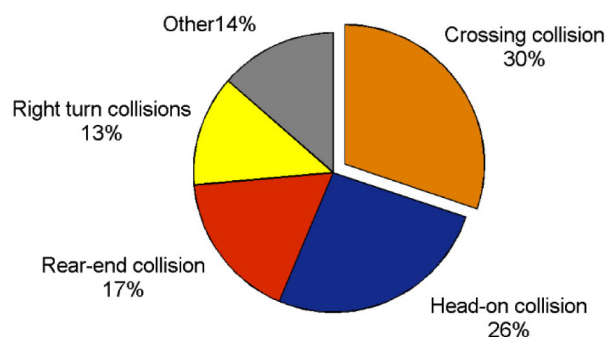
Various driver models have been proposed in order to quantitatively acquire the driving actions of drivers. For example, the transfer function-based model; the cross-over model; the look-ahead driver model; the fuzzy model; the neural network model; and so on. Also, in these days, the process of recognition, judgment and action of a driver is modeled to study the effectiveness of a driving assist system. This study aims at modeling a driver's braking actions by focusing on the Neural Network (hereinafter referred to as "NN") and the Time Delay Neural Network (hereinafter referred to as "TDNN"), which provide for building non-linear controlled models with the objective of building a model of a driver's braking actions.

NN enables the anticipation of an optimal solution at the moment through learning input and output data. Generally, it is frequently used in pattern matching, including image recognition. TDNN enables building a high accuracy model through learning from the present and past time-series data. At present, it is widely used in robot navigation [6], voice recognition [7], and production of models simulating traffic jams. The driver's braking actions are also included as time-series data, so this study used TDNN to build a model. A scenario of vehicle-to-vehicle collision accidents was modeled for rear-end collisions, which represent a high percentage among the vehicle-to-vehicle accidents in Japan, particularly those collisions where leading vehicles are stationary on a

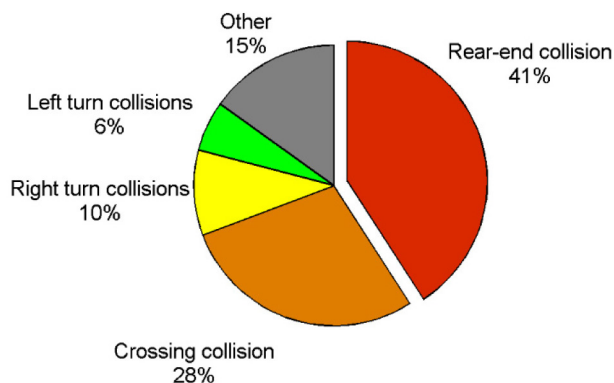
highway, which are an exceptionally high percentage. Also, in order to demonstrate the effectiveness of TDNN, an NN model under the same conditions was built for comparison to review the accuracy of the model. This study investigated the effectiveness of four parameters of a TDNN model: the number of learning; the number of neurons in hidden layers; sampling time; and the number of delay that shows the number of the past data. The evaluation of the driver model used the coefficient of determination that shows the suitability of a model.

Forms of Rear-End Collision Accidents in Japan

Though the number of road fatalities in Japan is on a downward trend, through advances in technologies such as active safety technology to forestall accidents and passive safety technology to mitigate accident damage, a total of 4,411 people were killed by traffic accidents in 2012. The majority of accidents were vehicle-to-pedestrian accidents or vehicle-to-vehicle accidents. [Figure 1](#) shows the vehicle-to-vehicle accidents in 2011 and the ratios of fatal accidents and injury accidents, including both serious and minor injuries [8]. It shows that the crossing collision and rear-end collisions are of high percentages. Consequently, the data of the above two types of accidents in the past ten years, including fatal accidents and serious and minor injuries, are shown in [Figure 2](#). It can be determined that the crossing collision among fatal accidents are declining and further decline can be anticipated, as the study on the Intelligent Transport System (ITS) that forestalls accidents through communication between roads and cars is actively underway. On the other hand, among fatal accidents, rear-end collisions do not show a downward trend, and thus we can expect the positive effect of regulated systems such as AEBS and CIB in the future. Therefore, this study places a focus on rear-end collisions, for which the positive effect of AEBS and CIB is anticipated, and surveyed accident data to grasp the situations of rear-end collisions. The situations of rear-end collisions can be divided into two types: one is the case where leading vehicles are stationary, while the other is the case where leading vehicles are in motion. [Figure 3](#) shows the ratios of each accident type. It shows that in fatal accidents, the cases of stationary leading vehicles are almost the same percentage as that of the cases of moving leading vehicles; whereas in accidents involving serious and minor injuries, the cases of stationary leading vehicles greatly exceed the cases of moving leading vehicles. Therefore, this study focused on stationary leading vehicles and modeled a driver's braking actions while the host vehicle approached the leading vehicle.

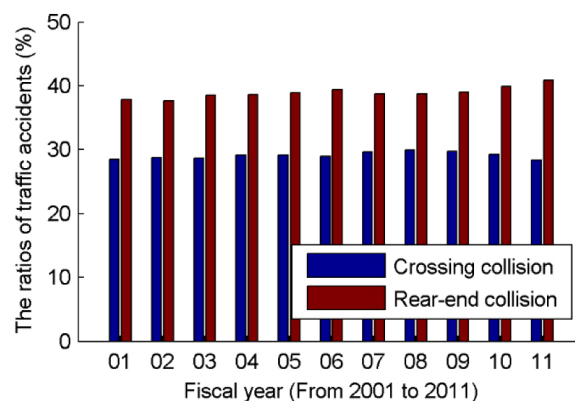


(a). The ratios of fatal accidents



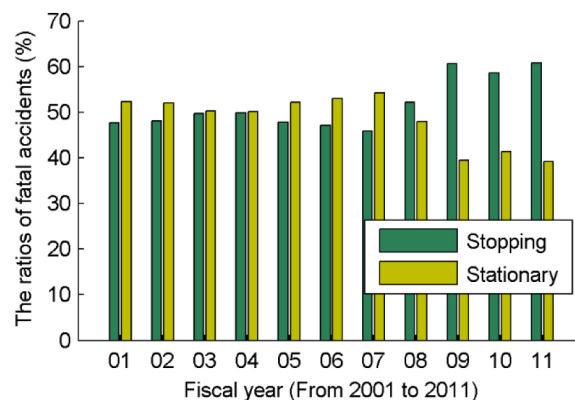
(b). The ratios of traffic accidents (Including serious and slight injury)

Figure 1. The ratios of traffic accidents when the vehicle collides with other vehicle (2011) [8]

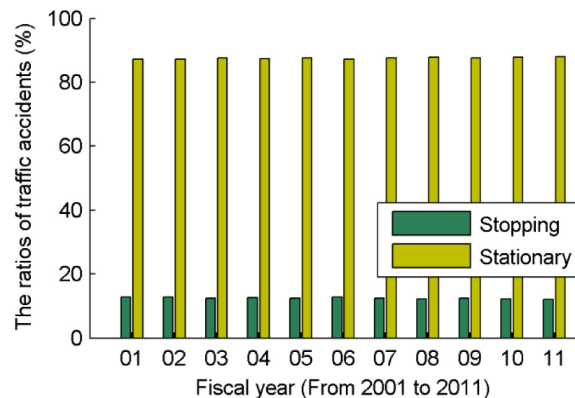


(b). The ratios of traffic accidents (Including serious and slight injury)

Figure 2. (cont.) The ratios of traffic accidents in rear-end collision and the crossing collision [8]

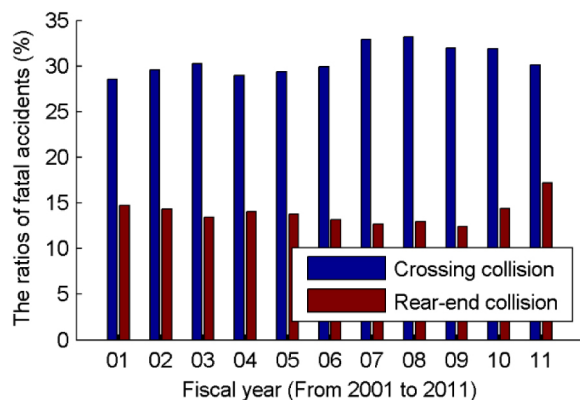


(a). The ratios of fatal accidents



(b). The ratios of traffic accidents (Including serious and slight injury)

Figure 3. The ratios of rear-end collision in case of the leading vehicle is moving and stationary [8]



(a). The ratios of fatal accidents

Figure 2.

BRAKING MODEL USING TDNN

TDNN and NN artificially express the characteristic functions of the nervous system of organisms, which provides for building a model by using teaching signals and input data. Thus, this study used TDNN and NN in building a model of driver's braking actions. TDNN is especially effective for modeling dynamic events, since the target of modeling is a driver's braking action that is time-series data.

Figure 4 shows the structures of TDNN and NN that are used in this study. TDNN consists of a three-layer structure: input layer, hidden layer and output layer. And, Table 1 show the parameters setup for TDNN and NN. As TDNN utilizes the present and past time-series data for learning, it has the number of delay (M) that shows to what extent the present and past data have been input into TDNN, and is able to use as input data $M+1$, which is the present data and the number of delay (M). Figure 5 indicates the relations between the number of delay (M) and sampling time of input data. Sampling time shows a cycle of measurement in measuring input data in experiments as time. From this, it shows that with maintaining a constant sampling time, the larger values in the number of delay (M) shows going back largely to the past, while the smaller M shows going back a little to the past, and it indicates the data of how many seconds ago were input into TDNN from the relations between the number of delay and sampling time. Then, if delay is assumed as l ($0 \leq l \leq M$), TDNN first calculates the sum of input, $S_{ji}(n)$, from the input data. $S_{ji}(n)$ can be expressed by the somethingth n learning of neuron j , somethingth i input data of $x_i(n)$ and the connection weight $w_{ji}(l)$, as shown below.

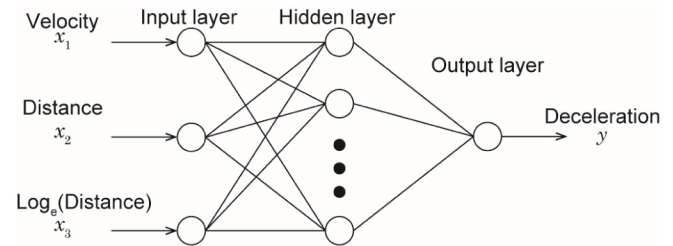
$$S_{ji}(n) = \sum_{l=0}^M w_{ji}(l) x_i(n-l) \quad (1)$$

From this, neuron j 's output v_j can be expressed in the following formula with putting p to the number of input data.

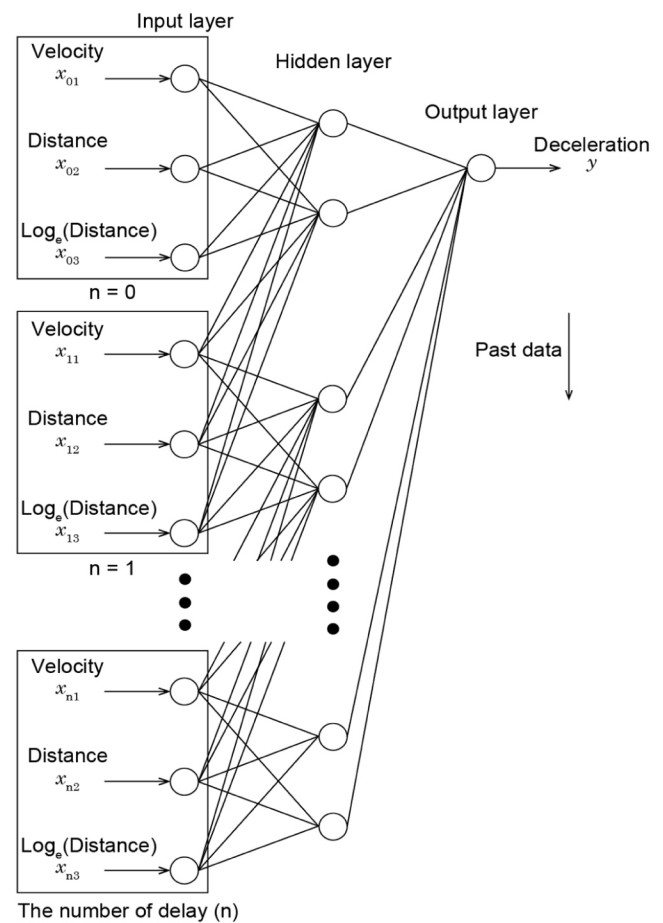
$$v_j(n) = \sum_{i=1}^p S_{ji}(n) - \theta_j \quad (2)$$

Then, θ_j is a threshold in neuron j . It can be found from this formula that in order to acquire a right output v_j , the connection weight $w_{ji}(l)$ needs to be updated. To update the connection weight $w_{ji}(l)$, a back-propagation learning method is employed. Also, as a method to converge calculation used in learning, a generally-used steepest descent method is employed. A driver

model was created under four parameters; the number of learning, the number of neurons in the hidden layers, sampling time and the number of delay (M) are set as parameters. In addition, an NN-based model was constructed with the aim to compare with TDNN [9].



(a). Neural Network (NN)



(b). Time Delay Neural Network (TDNN)

Figure 4. Neural Network and Time Delay Neural Network for constructing the driver model