

## Research Article

# The Implementation of Driver Model Based on the Attention Transfer Process

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To describe the characteristics of driver's attention changing with driving environment, establish the relation between driver model parameter and driver's attention, seek for mapping relation between driver's behavior and vehicle's running status data, and provide individualized driver simulation model for unmanned car controller or for driver's mental state inversion based on vehicle's running status data, the paper established a driver model based on driver's attention and deduced the relation between attention intensity and continuous driving time according to the process of driver's attention change from concentration to distraction and the distribution characteristics of their durations. The relationship between driver's mental state and manual closed-loop driving model parameters is established according to the transfer rule of attention in the driving course, and it is applied to driver model based on dynamical regulation neural network. Finally the paper researched dynamics evolution characteristics of vehicle running caused by fatigue driving in the environment of double lane change and large curvature, with test result verifying the effectiveness and accuracy of the driver model based on the attention transfer process.

## 1. Introduction

With the rapid development of artificial intelligence, breakthrough has been made in research on unmanned car, which is a smart auto that perceives road environment through on-board sensing system, automatically plans travel way, and controls the vehicle to arrive at predetermined destination. The unmanned vehicle technology is the fruit of high development of computer science, pattern recognition, and intelligent control technology and also an important mark to measure a country's scientific research strength and industrial level, with wide application prospects in national defense and economy domain. The on-board control system of unmanned technology can be regarded as a virtual driver, and to evaluate the performance of unmanned control system, the behavior characteristics of real driver's controlling of vehicle need to be considered. Development of unmanned technology provides diversified research angles for the research on characteristics of driver, while the research on characteristics of driver can provide the theoretical support for unmanned technology in terms

of principle of driver's characteristic to boost development of unmanned technology. When verifying principle of unmanned car's control module, it needs to use principle model or experiment vehicle or to be conducted on virtual driving simulator of high-performance vehicle. These experiments are relatively time-consuming and costly. Another option is to establish proper driver's behavioral model to substitute real driver from the perspective of computer simulation and substitute costly and time-consuming real-car experiment, thereby greatly shortening R&D cycle of the on-board control system. Thus, how to establish a mathematical model conforming to driver's behavioral characteristic is the core problem in the research.

Driver's driving behaviors can be divided into the longitudinal behavior and the horizontal behavior. The former one refers to the driver's accelerate-skid operating characteristic and car-following to keep safe driving, while the latter one refers to driver's turning corner and steering wheel operation to change the lane. Existing development progress for modeling approach of longitudinal driving behavior includes the following: during 2003~2004, Brackstone issued

several papers and systematically put forward the theory of describing longitudinal driving behavior using comprehensive safe interval holding mode and vehicle's longitudinal following model [1–3]. Longitudinal driving model can be regarded as a follow-up control system, thereinto, input is the safe interval expected by the driver, and output is actual safe interval. The controller (driver) controls throttle brake or gear according to difference between input and output to realize longitudinal following of target vehicle. Generally just two-order lag frequency model can reflect the driver's characteristics (hesitation period), reaction speed, and so forth. To reflect longitudinal driving characteristics at different running speeds, the high order lag frequency model can be adopted [4]. In practical application of longitudinal running behavioral model, the interference problems caused by measurement noise and habitual movements must be solved. To cope, some researchers apply Kalman filter, wavelet analysis based on multiscale, shape filter, and so forth for pretreatment. In offline research, progressive mean method can also be used to remove the above interference.

The above mathematical modeling research is all based on the mode of analysis. To match fuzzy behavior in driver's longitudinal operation behavior, some scholars put forward fuzzy control system to describe driver's behavior. This method is to fuzzify the methods of longitudinal driving rule utilization membership grade function and the domain of discourse, in practical application to establish fuzzy controller of longitudinal driving behavior to improve adaptability of vehicle's longitudinal following system [5].

The existing progress for modeling approach of horizontal driving behavior includes the following: in 1981, MacAdam put forward optimal preview control (OPC) in which all parameters except preview time can be defined by automobile dynamics [6]. This model is derived based on the condition of orbit's follow sum squared error, with orbit error follow precision able to meet physical demand. In 1993, Guo and Guan put forward preview optimization directional control driver model [7]. In 1996 MacAdam and Johnson put forward motor steering intelligent control system based on neural network and preview sensor [8], which obtained data of vehicle's position relative to road boundary and operational data of steering wheel through image sensor and then used artificial neural network to learn the obtained sample data. The neural network after learning can simulate the driver's horizontal driving behavior. In 2003 academician Guo and his students put forward preview optimization neural network driver model [9]. The principle problem for application of horizontal driving model is how to obtain driver's expected trajectory and actual trajectory of vehicle's running in real time. Currently the related research acquired the data through vision sensor and gyroscope [10]. Aiming at that real driver has flexibility and fuzziness, some researchers shifted research perspective to fuzzy control direction in recent years to utilize fuzzing mathematics and its relevant control theory to describe driver's control behavior [11]. Besides, there are also driver models based on adaptive control and AR model based on time series. And with the development of intelligent control theory, some scholars put forward horizontal driver

model combining fuzzing mathematics and neural network control [12, 13].

Longitudinal/horizontal driving behavioral model is to simply classify driver's driving behaviors into horizontal and longitudinal forms for study. However, the real situation of the driving behavior is complicated. For example, in complicated city road condition, one must consider to follow the front car and how to change the lane in traffic. When parking in congested parking lot, one must use kinematic trajectory planning to control the vehicle [14]. For the actual conditions of vehicle in complicated condition, some scholars put forward using characteristic of fuzzy system [15] and neural network [16] of strong nonlinear mapping capacity to build planning system of vehicle trajectory to meet the requirements on controlling horizontal and longitudinal directions in vehicle's motion control course, fuse longitudinal and horizontal driving behaviors, and establish uniform driving behavioral model.

Above is all in normal driving condition without considering the driving course deterioration caused by continuous driving or random variation characteristics of driver's behavior caused by uncertainties of environment. To depict the relation between driver's intent and road environment and understand evolution rule of driver's attention in the driving course, the paper came up with the time and space distribution of driver's attention based on Markov Model and established the relationship between driver model parameter and driver's attention. To illustrate the randomness and individuation of driver model, model support is provided.

## 2. Driver Model Based on the Attention Transfer Process

Figure 1 is the basic block diagram of driver model in the course of distraction. The driver tries to focus on long-term and high-load driving mission. Yet due to interference of various factors (physiology, psychology, fatigue, etc.), the driver's attention would be attracted by other things, leading to brief loss of information processing power. Later due to the vigilance mechanism, the driver spontaneously diverts attention to driving information processing. Meanwhile, driver's information processing course is a repeated course composed of preview link (information perceiving), judge link (judgment and making decision), and action link (action output).

Notwithstanding driver's driving behavior is very complicated, a qualified driver's action is not messy and evasive, and it is guided by certain driving principle which appears as common characteristics of driver and can be described using driver model. Further identification research of driver model parameter shows that, for specific driver, the parameters of driver model are not unchanging but display normal random distribution in certain interval. When the driver's attention is concentrated, the values of its model parameters are stable, and variance is small; when the driver's attention is not concentrated or stable, the identification result of driver model parameters shows variance of model parameter is large. Assuming the variance of preview time in preview link

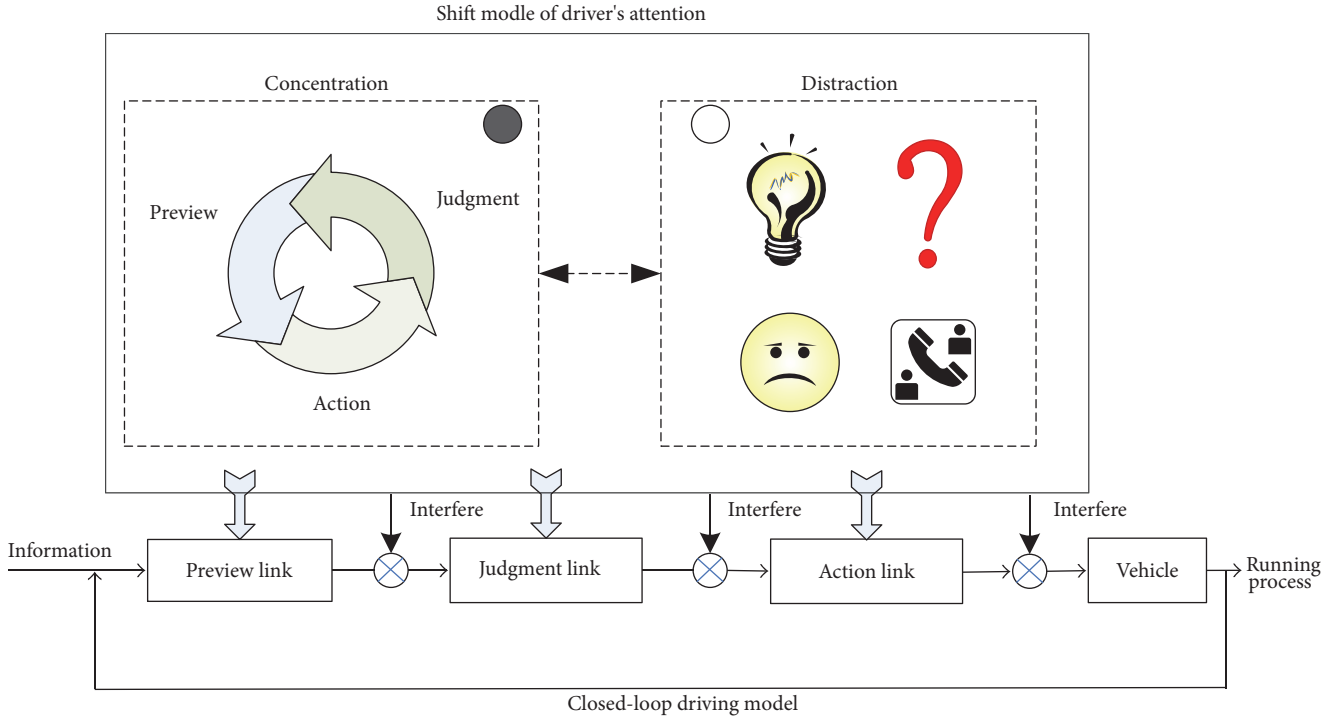


FIGURE 1: The basic skeleton diagram of driver model with driver's attention.

$T_p$ , thinking delay time in judgment link  $t_d$ , and inertial delay time in action link  $T_h$  is in proportion to distribution probability of driver's attention in corresponding link. In mathematical language, the above idea can be expressed as

$$\begin{aligned} t_d(t) &\sim N(\bar{t}_d(t), \sigma_{td}(t)) \\ T_h(t) &\sim N(\bar{T}_h(t), \sigma_{T_h}(t)) \\ \sigma_{td}, \sigma_{T_h} &\propto \tilde{P}_i(t), \end{aligned} \quad (1)$$

where  $t_d(t)$ ,  $T_h(t)$  are driver's neuro and action reaction time at time  $t$ ;  $\bar{t}_d(t)$ ,  $\bar{T}_h(t)$  are driver's average neuro and action reaction time at time  $t$ ,  $\sigma_{td}(t)$ ,  $\sigma_{T_h}(t)$  are variance of driver's neuro and action reaction time at time  $t$ ,  $\tilde{P}_i(t)$  is the probability of driver's attention being concentrated in specific link at time  $t$ .

Different values of driver's preview time  $T_p$ , delay time  $t_d$ , and inertial delay time  $T_h$  embody different driver's characteristics in different driving environments. For example, increase of driver's average delay time at  $\bar{t}_d(t)$  and inertial delay time  $\bar{T}_h(t)$  means the driver is in fatigue or drunken state. The magnitude of variances of driver's neuro and action reaction time  $\sigma_{td}(t)$  and  $\sigma_{T_h}(t)$  means the driver's attention concentration.

If we can find probability of distribution of driver's attention in links of preview, judgment, and action, according to formula (1), in theory, we can construct probability statistics rule between driver model parameters based on driver's distraction course and establish the relation between closed-loop driver model parameters and driver's attention in statistic significance.

From this, we know to build the driver simulation model that protects driver's attention factor, and we should firstly research distribution rule of probability of driver focusing attention to drive according to the course of attention distraction and upgrading, to get time migration rule of attention  $A(t)$ , and to find the space migration rule  $P_i$  through research on the jump rule in the link of preview-judgment-action.

From this we can get the probability of driver focusing attention in a specific link.

$$\tilde{P}_i(t) = P_i \cdot A(t), \quad (2)$$

where  $A(t)$  is the probability of driver's attention being concentrated;  $P_i$  is the probability of driver's attention being focused in link  $i$  at  $t$ .

Then according to formula (1) we can build the probability statistics rule between driver's attention index and driver model parameters and establish the relation between closed-loop driver model and driver's attention index in statistic significance.

### 3. Migration Model of Driver's Attention

**3.1. Driver's Attention Declines.** The driver tries to pay attention to the long-term and high-load driving mission. Yet due to interference of various factors (physiology, psychology, fatigue, etc.), the driver's attention would be attracted by other things, leading to a brief loss of information processing power. Later due to own vigilance mechanism, the driver spontaneously diverts attention to driving information processing. The course of diverting and upgrading attention is shown in Figure 2.

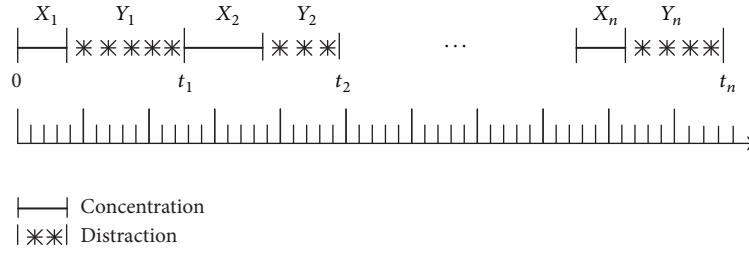


FIGURE 2: The schematic diagram of driver's attention update.

First, assuming driver's attention is concentrated in the initial time ( $t = 0$ ), the probability of duration  $X_i$  of driver keeping concentrated attention obeys  $F(t)$  distribution; the probability of duration  $Y_i$  of driver's attention being not concentrated obeys  $G(t)$ ; therinto  $i = 1, 2, \dots, N$  is cycle numbers; the point of shifting from concentrated to not concentrated is regarded as regeneration point of attention.

Set status space of driver's attention concentration as  $E = \{0, 1\}$ , and  $X(t)$  means the status of attention at time  $t$ . Therinto,  $X(t) = 0$  means attention is not concentrated;  $X(t) = 1$  means attention is concentrated. Attention concentration and distraction are alternating. Figure 2 intuitively expresses this updating course; therinto,  $t_1, t_2, \dots, t_n$  are all at critical points of attention updating process. Figure 2 tells us that the time span of the  $i$ th updating cycle is

$$Z_i = X_i + Y_i. \quad (3)$$

According to assumption of  $\{Z_i\}$  ( $i = 1, 2, \dots, N$ ) being random variable series which have same distribution and are independent from each other, the probability  $P\{Z_i \leq t\}$  of its updating cycle being smaller than  $t$  is

$$\begin{aligned} Q(t) &= P\{Z_i \leq t\} = P\{X_i + Y_i \leq t\} \\ &= \int_0^t G(t-u)F(u)du = G(t) * F(t), \end{aligned} \quad (4)$$

$$i = 1, 2, \dots, N.$$

Set  $A(t)$  as the probability of driver's attention being concentrated at  $t$ ; that is,  $A(t) = P\{X(t) = 1 \mid X(0) = 1\}$ ; using total probability formula, we get

$$\begin{aligned} A(t) &= P\{X_1 > t, X(t) = 1 \mid X(0) = 1\} \\ &+ P\{X_1 \leq t \leq X_1 + Y_1, X(t) = 1 \mid X(0) = 1\} \\ &+ P\{X_1 + Y_1 \leq t, X(t) = 1 \mid X(0) = 1\}. \end{aligned} \quad (5)$$

Referring to Figure 2, we classify it into three conditions for discussion.

When driver's attention is concentrated,

$$P\{X_1 > t, X(t) = 1 \mid X(0) = 1\} = 1 - F(t). \quad (6)$$

When  $X_1 \leq t \leq X_1 + Y_1$ , driver's attention at time  $t$  is sure to be concentrated.

$$P\{X_1 \leq t \leq X_1 + Y_1, X(t) = 1 \mid X(0) = 1\} = 0. \quad (7)$$

When  $X_1 + Y_1 \leq t$ , from conditional expectation formula, we can get

$$\begin{aligned} P\{X_1 + Y_1 \leq t, X(t) = 1 \mid X(0) = 1\} &= \int_0^t P\{X(t) \\ &= 1 \mid X(0) = 1, X_1 + Y_1 = u\} dP\{X_1 + Y_1 \leq u\} \\ &= \int_0^t A(t-u)Q(u)du = Q(t) * A(t). \end{aligned} \quad (8)$$

Synthesizing above discussions, we know that

$$A(t) = 1 - F(t) + Q(t) * A(t). \quad (9)$$

$F(t)$  is probability distribution of time duration  $X_i$  of driver keeping attention, and  $G(t)$  is distribution of time duration  $Y_i$  of the driver being not concentrated. According to assumption of subsequent distribution being unrelated to previous state, distribution state has no memory, and exponential distribution has no memory, so the two time distribution assumptions obey exponential distribution. To expand freedom degree of distribution, this two-parameter distribution of exponent is selected, and the density function of its distribution is

$$\begin{aligned} f(t) &= \frac{1}{\sigma_1} e^{-(t-\mu_1)/\sigma_1}, \quad t > \mu_1, \sigma_1 > 0 \\ g(t) &= \frac{1}{\sigma_2} e^{-(t-\mu_2)/\sigma_2}, \quad t > \mu_2, \sigma_2 > 0, \end{aligned} \quad (10)$$

where  $\mu_1, \mu_2, \sigma_1, \sigma_2$  are distribution parameters, whose values are different in different driving environments and psychological states, and can be calibrated through experiment. Substitute formula (10) into (9) for Laplace transformation. After arrangement, we get

$$A(s) = \frac{\sigma_1 \sigma_2 s^2 + (\sigma_1 + \sigma_2 - \sigma_2 \cdot e^{\mu_1/\mu_2})s + e^{\mu_1/\sigma_1}}{\sigma_1 \sigma_2 s^3 + (\sigma_1 + \sigma_2)s^2 + (1 - e^{\mu_1/\sigma_1 + \mu_2/\sigma_2})s}. \quad (11)$$

From the above, we can get the probability of driver's attention being concentrated at  $t$ .

$A(t) = L^{-1}(A(s))$ , taking inverse transformation of Laplace transformation for formula (11) to get



FIGURE 3: Schematic diagram of driver's attention shift.

$$A(t) = \frac{C_1 \cdot S_q + (2 \cdot B_1 \cdot C_2 - B_2 \cdot C_1 - B_2 \cdot C_2) \cdot \sinh\left(\left(\frac{S_q}{2}\right) \cdot t\right) \cdot e^{-(B_2/2)t}}{C_2 \cdot S_q} + \frac{(C_2 - C_1) \cdot \cosh\left(\left(\frac{S_q}{2}\right) \cdot t\right) \cdot e^{-(B_2/2)t} \cdot S_q}{C_2 \cdot S_q}, \quad (12)$$

where

$$\begin{aligned} B_1 &= \frac{(\sigma_1 + \sigma_2 - \sigma_2 \cdot e^{\mu_1/\mu_2})}{(\sigma_1 \cdot \sigma_2)} \\ B_2 &= \frac{(\sigma_1 + \sigma_2)}{(\sigma_1 \cdot \sigma_2)} \\ C_1 &= \frac{e^{\mu_1/\sigma_1}}{(\sigma_1 \cdot \sigma_2)} \\ C_2 &= 1 - \frac{e^{\mu_1/\sigma_1 + \mu_2/\sigma_2}}{(\sigma_1 \cdot \sigma_2)} \\ S_q &= \sqrt{B_2^2 + 4 \cdot C_2}. \end{aligned} \quad (13)$$

**3.2. Attention's Space Migrating Model in Driving Course.** Attention randomly jumps in three links of preview, judgment, and action in the driving course of driver. The process is as shown in Figure 3.

Set driver's attention shifting state space  $E = (0, 1, 2)$ ; here 0 represents preview link, 1 represents judgment link, and 2 represents action link. The driver's attention transfers with preview link as center. From this, we can get following shifting logic: when shifting time approaches zero, attention shifts with other links only with preview link as center. The shifting between action link and judgment link needs longer time on the basis of above shifting. Set distribution function of time duration  $T_i$  during which time attention leaves the  $i$ th link from link  $a$  to  $b$  as  $F_i(t)$  and distribution function of time duration  $\tau_i$  during which time the attention rests at the  $i$ th link as  $G_i(t)$ . Experience proves that resting of driver's attention and its deviation time obey exponential distribution, and its shifting course is very similar to Markov process. So Markov process can be used to solve state vector of driver attention's distribution in each link at specific time.

First define the distribution function of time duration  $T_i$  during which time attention leaves the  $i$ th link in links  $a$  to  $b$  as  $F_i(t)$  and the distribution function of time duration

$\tau_i$  during which time attention rests in the  $i$ th link as  $G_i(t)$ . Large amount of experiment data show that the two time distributions obey exponential distribution; set their distribution function as

$$F_i(t) = 1 - e^{-\lambda_i t}, \quad i = 1, 2 \quad (14)$$

$$G_i(t) = 1 - e^{-\mu_i t}, \quad i = 1, 2.$$

Defining of shifting rate  $a_{ij}$  can be divided into four conditions.

Using the combinatorial event probability, we can decompose the conditions as follows.

At time  $t$ , the driver's attention is in the main concentration link-preview link and still in this link at time  $t + \Delta t$ .

$$\begin{aligned} P_{00}(\Delta T) &= P\{X(t + \Delta t) = 0 \mid X(t) = 0\} \\ &= P\{T_1 > \Delta t, T_2 > \Delta t\} = e^{-(\lambda_1 + \lambda_2)\Delta t} \\ &= 1 - (\lambda_1 + \lambda_2) \cdot \Delta t + o(\Delta t). \end{aligned} \quad (15)$$

At time  $t$ , the driver's attention is in the main concentration link-preview link and is in the  $i$ th link at time  $t + \Delta t$ .

$$\begin{aligned} P_{0i}(\Delta T) &= P\{X(t + \Delta t) = i \mid X(t) = 0\} \\ &= P\{T_i \leq \Delta t\} = 1 - P\{\tau_i > \Delta t\} = 1 - e^{-\mu_i \Delta t} \\ &= \mu_i \Delta t + o(\Delta t). \end{aligned} \quad (16)$$

At time  $t$ , the driver's attention is in  $i$ th link (preview or action) and is still in the  $i$ th link at time  $t + \Delta t$ .

$$\begin{aligned} P_{jj}(\Delta T) &= P\{X(t + \Delta t) = j \mid X(t) = j\} \\ &= P\{\tau_j > \Delta t\} = e^{-\mu_j \Delta t} = 1 - \mu_j \Delta t + o(\Delta t). \end{aligned} \quad (17)$$

At time  $t$ , the driver's attention is in link  $i$  and is in the  $j$ th link at time  $t + \Delta t$ .

$$\begin{aligned} P_{i,j}(\Delta T) &= P\{X(t + \Delta t) = j \mid X(t) = i\} \\ &= P\{T_j \leq \Delta t, \tau_i \leq \Delta t\} \\ &= (1 - e^{-\lambda_j \Delta t}) \cdot (1 - e^{-\mu_i \Delta t}) = o(\Delta t). \end{aligned} \quad (18)$$

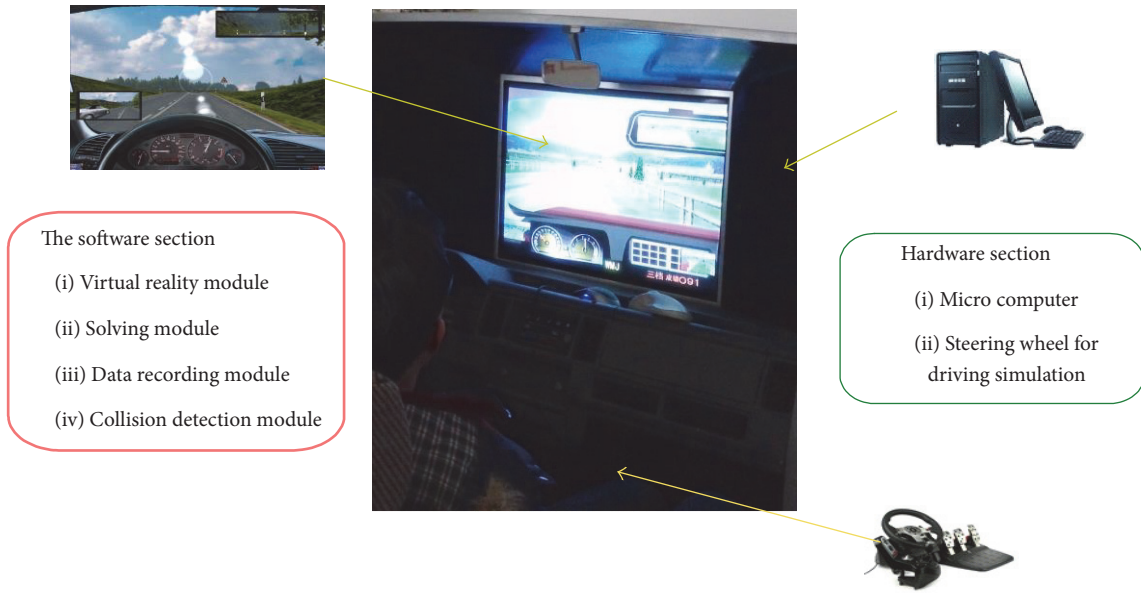


FIGURE 4: The driving simulator.

To sum up, we can get expression of shifting probability matrix  $\mathbf{A}$ :

$$\mathbf{A} = \begin{bmatrix} -\lambda & \lambda_1 & \lambda_2 \\ \mu_1 & -\mu_1 & 0 \\ \mu_2 & 0 & -\mu_2 \end{bmatrix}. \quad (19)$$

Establish differential equation according to Markov's related theories:

$$\mathbf{P}'(t) = \mathbf{P}(t) \mathbf{A}. \quad (20)$$

Initial conditions are

$$\{P_0(0), P_1(0), P_2(0)\}. \quad (21)$$

Subject both sides of formula (20) to Laplace transformation to get

$$\begin{aligned} sP_0^*(s) - 1 &= -\lambda P_0^*(s) + \mu_1 P_1^*(s) + \mu_2 P_2^*(s) \\ sP_i^*(s) &= \lambda_i P_i^*(s) - \mu_i P_i^*(s), \quad i = 1, 2. \end{aligned} \quad (22)$$

Solve this linear equation and subject it to Laplace inverse transformation to get

$$\begin{aligned} P_0^*(s) &= L^{-1} \left( \frac{1}{s + s \sum_{i=1}^n (\lambda_i / (s + \mu_i))} \right) \\ P_i(t) &= L^{-1} \left( \frac{\lambda_i}{s + \mu_i} P_0^*(s) \right). \end{aligned} \quad (23)$$

#### 4. The Parameter Identification of Driver's Attention Migration Model

Driver's attention evolution model and attention distribution model consists of a set of equations with undetermined parameters, such as (14) and (23).

It is worth noting that the parameters of the model, which represent the pilot population, are not the parameters of a single driver, so it is necessary to have different drivers to get the identification parameters. If we want to build a real vehicle experimental environment with different road conditions, there is a high cost and uncontrollable safety factor, so the driver's characteristics research is generally carried out in a simulated driving environment.

Currently, simulating driving machine is a common way of training driver, which can embody close-loop driving characteristic of people-vehicle-road. Most of the current research literatures about driver's behavior adopt simulating driving machine as one of the primary experimental media. The function of simulating driving machine mainly constitutes a virtual driving environment and gets response to driver's real driving action and control state by virtual input of different roads, dynamic properties, and environment. Thus it proved that simulating driving machine can be used to research driver's attention in driving process. The structure of simulating driving machine adopted in this paper is shown in Figure 4.

*4.1. The Parameter Calibration Methods for Driver's Attention Declines Model.* Attention focused test is used to identify the parameters of the driver's attention distribution. The specific experimental process is as follows: red, yellow, and green signal lights were placed in front of the driver and the driver is asked to make a response immediately when the signal is seen. Red signal is to press the A key, the yellow signal to press the B key, the green signal to press the C key, and record the duration of the driver's attention.

30 typical drivers, with the driver's age between 20 to 35 years, according to the gender of the driver, are divided into 2 groups.

Record the time of the driver's attention concentration  $X_i$  and distraction  $Y_i$ , respectively. In this way, we can estimate

TABLE 1: Parameter estimation of distribution function.

Gender	Distributed parameter			
	$\sigma_1$	$\sigma_2$	$\mu_1$	$\mu_2$
Male	30.236	10.436	12.543	-129.84
Female	32.389	7.806	11.954	-131.96

the parameters of distribution function by the sample distribution frequency histogram. The distribution function of the driver's attention concentration time  $F(t)$  can be written as a discrete density function:

$$f(t) = \begin{cases} 0 & 0 < t < c_1 \\ f_z & c_z \leq t \leq c_{z+1} \\ f_{n1} & t \geq c_{n1} \end{cases} \quad z = 1, 2, \dots, n_1 - 1, \quad (24)$$

where  $c_z$  is the demarcation point selected by frequency histogram sample data;  $n_1$  is the total of division points for frequency histogram sample data,  $f_z$  is the frequency by which the lasting time of driver's attention being concentrated falls in time interval  $[C_z, C_{z+1}]$ .

Similarly,  $G_i(t)$ 's discrete density function can be expressed by frequency histogram. After getting frequency chart, we can use knowledge related to parameters estimation to estimate parameters of probability model. Table 1 is estimated values for parameters of  $f(t)$ ,  $g(t)$  distribution function of male and female drivers.

**4.2. The Parameter Calibration Methods for Driver Attention Migrating Model.** The probability of driver's attention resting at one certain link can be realized by setting mask program at one link, such as setting mask program for preview link (after the program runs, the road part of simulating driving machine becomes black) and mask program of operation directive (after the program runs, action directive becomes void). The principle is that when the tested driver finds it, driver can click a button to obtain a period of time of mask program opening. The computer will take down the time of pressing switch and then the frequency by which the driver's attention rests in one link can be obtained by the gathered statistic data.

Set the distribution function of time duration during which time the driver leaves the  $t$ th link, and set distribution function of time duration  $\tau_i$  during which time the driver rests at the  $i$ th link as  $G_i(t)$ . Define parameters of distribution function  $F_i(t)$ . The probability theory can be combined. Use sample distribution frequency histogram to estimate value of parameters of distribution function.  $F_i(t)$ 's discrete density function is shown in (24).

Similarly,  $G_i(t)$ 's discrete density function can be expressed by frequency histogram. After getting frequency chart, we can use knowledge related to parameters estimation to estimate parameters of probability model.

Divide drivers into two groups by gender. After 6 hours of continuous experiment, test drivers' probability index of

TABLE 2: Attention parameters in various driving conditions.

Route	Distributed parameter			
	$\lambda_1$	$\lambda_2$	$\mu_1$	$\mu_2$
Straight line	0.105	0.058	1.000	1.000
Lane change	0.147	0.088	0.500	0.500
Intersection	0.125	0.137	0.333	0.333

attention concentration, respectively. Thereinto, the parameters of distribution function  $f_i(t)$ ,  $g_i(t)$  are estimated by frequency histogram. Table 2 is estimated values for parameters of  $f(t)$ ,  $g(t)$  distribution function of male and female drivers.

#### 4.3. The Parameter Identification Methods for Driver Model.

The driver is the crucial link in the closed-loop system of people-car-road. Thus, an advance optimization of artificial neural network was carried out based on identification of the key parameters of driver model, which actually belong to the problem of closed-loop system parameter identification. According to the closed-loop system identification theory, if the input/output subsystems of the closed-loop system are measurable, the suitable method of open-loop identification can be adopted. The measurement of the input and output of the subsystem model is set up directly (direct identification method). At present, the model parameter identification method is usually divided into frequency domain and time domain method: the frequency domain method is mainly through Fourier to transform the original data. And input and output transform exist in frequency domain, and then the frequency response of the system is to simulate nonlinear parameters and the characteristics. Its precision mainly depends on the estimation and precision of the frequency characteristics. The basic idea of the time domain identification implies using the finite difference model ARMA (autoregressive moving average) equation for least squares identification of input and output data, and then do Z transform to define transfer function for a discrete system. In this paper, in the time domain, it is by using quantum genetic algorithm that the global evolutionary optimization method and identification of parameters for model of direct control over the pilot are realized. There is neither a need for changes in frequency domain, nor deviation from transformation to improve the precision of parameter identification accuracy. More importantly, parameters for the natural driver are identified to involve in the operation of the object driver vehicle model.

The actual vehicle model (or driving simulation) tends to be very complicated due to the unavailability of the software for the mathematical description model of vehicle. As a result, it will not be able to directly calculate the pilot model parameters, which are needed for the vehicle model. So before applying the pilot model, it is necessary to simplify the complex vehicle model. Also, since the complex vehicle model is equivalent to two-degree-of-freedom linear vehicle model, according to the theory of system parameter identification method, the pilot model which is needed for vehicle kinetic parameters identification of the model can be calculated.

Figure 7(b) illustrates the vehicle model parameter identification block diagram and its specific identification process is as follows: select a typical vehicle steering wheel angle signal  $\delta_{sw}$  (or a set of test data of the vehicle) and then input it to the vehicle model of complex system, with lateral acceleration  $a_y$  of the vehicle as the output of the system. And tie the same steering wheel angle, and then input it to the equivalent of two-degree-of-freedom vehicle model. The square sum of the difference between the measured lateral acceleration  $a_{y1}$  and the acceleration of the model output  $a_y$  is as an optimized target function, so as to optimize the parameters of vehicle model.

According to the static conditions based on literature [17], the equation can be shown in Figure 6 in which driver closed-loop optimization model of artificial neural network is converted into open-loop form, as shown in Figure 7.

The relationship between advanced pilot model and the weights of optimized neural network is not isolated. On the contrary, there is a certain link between time lag link with the driver, car, and structural parameters. By combining the neural network model under the static condition with [17], the relationship between the driver motor closed-loop system and the parameters can be obtained.

$$\begin{aligned} w_{11} &= -w_{12} = 1 \\ w_{13} &= -T_p \\ w_{14} &= K_0 - \frac{T_p^2}{2} \\ K_0 &= \frac{T_p^3}{(6 \cdot T_{q1})}. \end{aligned} \quad (25)$$

From (25), it is shown that there is close relationship between pilot model with the values, parameters  $K_0$ , and the driver's time lag link  $T_{q1}$  (including the driver model and the structural parameters of the vehicle information). Among them, the relationship between driver model parameters  $T_{q1}$  and  $T_{q2}$  is as follows:

$$\begin{aligned} T_{q1} &= T_h + t_d + T_1 - T_{y1} \\ T_{q2} &= T_h \cdot T_1 + \frac{t_d^2}{2} + (t_d - T_{y1}) \cdot (T_h + T_1 - T_{y1}) \\ &\quad + T_2 - T_{y2}. \end{aligned} \quad (26)$$

Of (26),  $T_h$ ,  $t_d$  are the time constants of the pilot model lag;  $T_1$ ,  $T_2$ ,  $T_{y1}$ ,  $T_{y2}$  are the parameters of the two-degree-of-freedom vehicle model.

When the driver model parameters are identified, the open-loop driver model and vehicle model are close to theoretical data, and the corresponding test data shows the optimization of objective function. Therefore, setting the optimization goal is essential for avoiding the steering wheel angle error, for the sum of squares of lateral acceleration error, for the error sum of squares, for the error sum of squares of lateral displacement, and the weighted values of the three  $J_E$ .

$$J_E = w_1 \cdot J_{e1} + w_2 \cdot J_{e2} + w_3 \cdot J_{e3}. \quad (27)$$

Of the equation,  $J_{e1} = \int_0^t (\delta_{sw} - \widehat{\delta}_{sw}) dt$  is the steering wheel angle error indicator;  $J_{e2} = \int_0^t (\ddot{y} - \widehat{\ddot{y}}) dt$  is the lateral acceleration error indicator;  $J_{e3} = \int_0^t (y - \widehat{y}) dt$  is the lateral displacement error indicator;  $\delta_{sw}$ ,  $\dot{y}$ ,  $y$  are the experimental data of a driving simulation experiments.  $\widehat{\delta}_{sw}$ ,  $\widehat{\ddot{y}}$ ,  $\widehat{y}$  are collected for open-loop driver model and vehicle model to calculate the theoretical data. Therefore,  $w_1$ ,  $w_2$ ,  $w_3$  are the weighted values, respectively, 0.8, 0.1, 0.1.

The identification problem of driver model parameters is converted to optimization problem, and the quantum genetic algorithm is used to optimize the parameters of the model [18].

Figure 8 shows the contrasting curve between car driving route in closed-loop driving experiments and parameter identification of the theory. The points on the graph line represent road center line, while the solid lines represent the car's actual movement track line. By using the theoretical identification of parameters and theoretical calculation of the trajectory path of experimental road and by using complex stretching of road grade into small and big curvature sections, we simulated the actual driving in the process of the different influence of a road camber on drivers' mind. The zoom graph shows in detail that, by using the theory of RCQGA, the parameters identification helps to calculate trajectory and the movement track of car that almost overlaps. All these illustrate the correctness of the driver parameter identification method.

## 5. Comparison of Experimental Data and Theoretical Calculation Result

Attention is the ability to purposively focus psychological activities on one thing for long. To judge the driver's concentration degree, we can implant a mask program in simulating driving machine. After the program runs, one region on the screen of driving machine becomes black. If driver's attention is concentrated, he can be aware of the existence of shield cover.

Then the tested driver can click button to get a period of continuous opening time  $t^0$  of shield cover. The value of attention index  $A_t$  can be obtained by calculating time difference  $t_i^c$  between the closing and reopening of shield cover. The formula expression is

$$\begin{aligned} A_t &= \frac{\sum_{i=1}^n (t^0 + \alpha_i t_i^c)}{\sum_{i=1}^n (t^0 + t_i^c)} \\ \alpha_i &= \begin{cases} 1 & t \leq t_r \\ 0 & t \geq t_r, \end{cases} \end{aligned} \quad (28)$$

where  $n$  is the times of shield cover opening in test period;  $t^0$  is the opening time of shield cover after setting button for one time;  $t_i^c$  is the interval of shield cover closing for the  $i$ th time to reopening,  $t_r$  is the average action reaction time from finding shield cover closed to pressing button to make shield cover reopen.



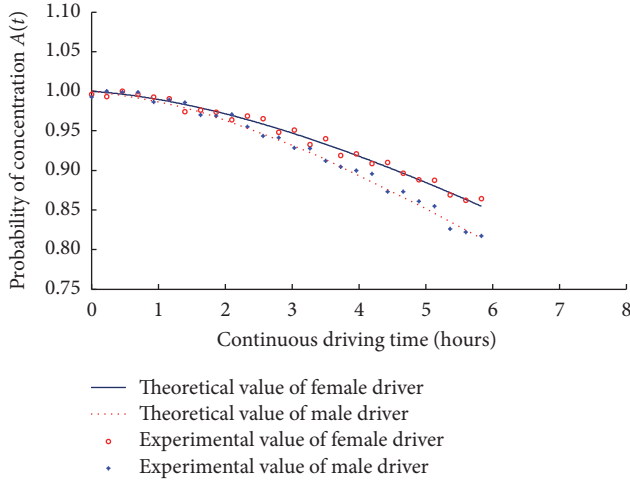


FIGURE 5: Comparison between theory and experiment.

The above method is adopted for measurement of driver's attention index. Select 15 representative drivers and group them according to gender. The drivers are aged from 20 to 35. The tested drivers are required to be repeatedly tested in specific simulating driving environment.

Figure 5 is comparison diagram of calculated value and experiment value for attention probability of male and female drivers in continuous driving. The figure shows that the error between ideal solution and experiment value is acceptable, proving theoretical equation is correct. Besides, the figure also tells us female drivers' attention is more stable than male drivers' attention.

Use the data in Table 2, set initial condition as  $P(0) = (1, 0, 0)$ , and substitute it into formula (23) and make Laplace inverse transformation to get three groups of state functions in each subdomain, altogether 15.

Then we can get vector function of driver's attention in linear driving state:

$$\begin{aligned} P_t(0) &= 0.140 \cdot e^{-1.163t} + 0.860 \\ P_t(1) &= -0.009 \cdot e^{-1.163t} + 0.090 \\ P_t(2) &= -0.0498 \cdot e^{-1.163t} + 0.005. \end{aligned} \quad (29)$$

When the time is long enough for driver to adapt to road condition, distribution state of driver's steady attention in different running states can be solved by formula (23), as shown in Table 3.

## 6. Application Example of Driver Attention Model

According to formula (23), we can get driver's attention distribution state in different running states. When the driver's attention is concentrated, the values of its model parameter are stable, and variance ratio is small; when the driver's attention is not concentrated or stable, identification result of driving model parameter shows variance ratio of model parameter is big. Then according to formula (1), we

TABLE 3: The steady distribution of attention parameters in various driving conditions.

Route	Preview link	Judgment link	Action link
Straight line	0.86	0.09	0.05
Lane change	0.68	0.20	0.12
Intersection	0.56	0.21	0.23

can get the relationship between driver model parameter and attention to establish driver closed-loop simulation model with attention as input.

Driver's attention state can migrate. To adapt to characteristics of emergency reaction for real driver, here we adopt drive model that has state reference device and includes limited condition.

Figure 6 is the driver model that has state reference device and includes limited condition, which is composed of driver model and limiting state adjustment link. Here the real line part is reduced form for driver model of preview neural network while the dotted part is limiting state adjustment link based on neural network.

**6.1. Driver Model Part.** The function of preview link  $e^{T_p s}$  is to simulate the actual condition of driver observing information of the road in the front in advance. The position of preview point in the front of vehicle is input  $f(x(t))$ . The function of lag link is to describe driver's characteristic of lag reaction; thereinto  $e^{-t_d s}$  represents reaction lag of driver's neuro system,  $t_d$  is lag time of neuro reaction;  $1/(1+T_h \cdot s)$  represents inertial lag link of driver's arm action and steering wheel response;  $T_h$  is time constant of inertial lag link.

**6.2. Vehicle Model Part.** When the skilled driver drives normally on dry and common road, the road sticks to good ground for running, with little change in dynamic behavior. Feedback adjustment link of dynamic adjustment neural network represented by the dotted part is inoperative, and its output is approximately zero. In other words, the reference dynamical model formed by adjustment link and the model's vehicle dynamical model has the same driving characteristics.

When driver's attention is distracted, which will lead to emergency reaction, the vehicle's dynamical characteristics are in limited condition. Side slipping or large deformation occurs between tyre and ground to cause change of vehicle's dynamical characteristics, making automobile dynamical model in driver model inconsistent with actual dynamical model. Dynamic neural network adjustment link begins to work (dotted part). The difference  $\Delta a_y$  between the lateral acceleration output by reference model and actual vehicle model and difference of lateral velocity  $\Delta v_y$ , and difference of lateral shift  $\Delta y$  are all not zero. The steering wheel correction value output by neural network link  $\delta_h$  is not zero. The adjustment link is in work state.

Neural network possesses nonlinear and self-adaptive characteristics, which guarantees that improved driver

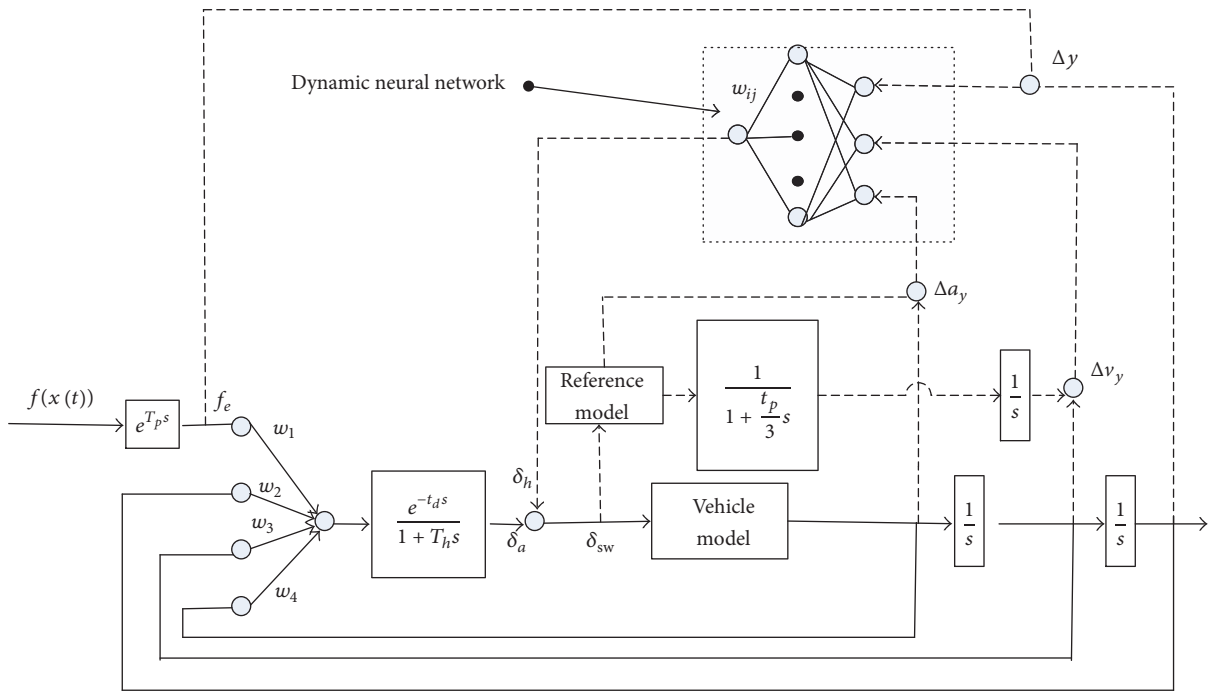
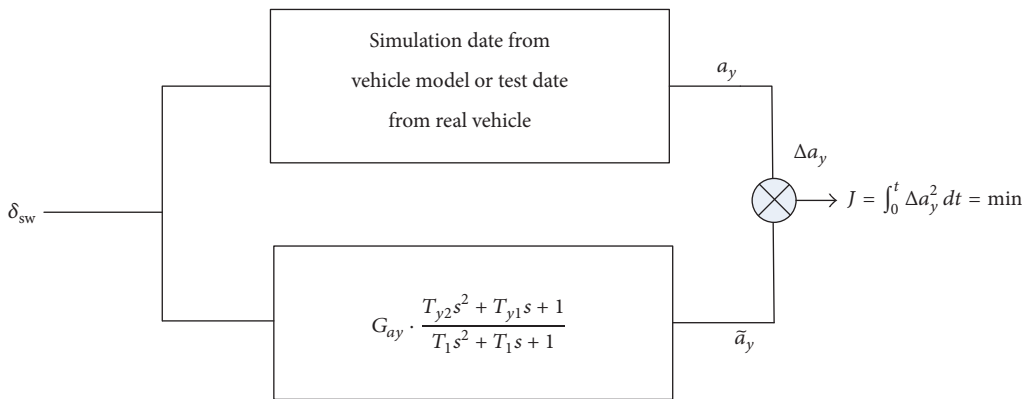
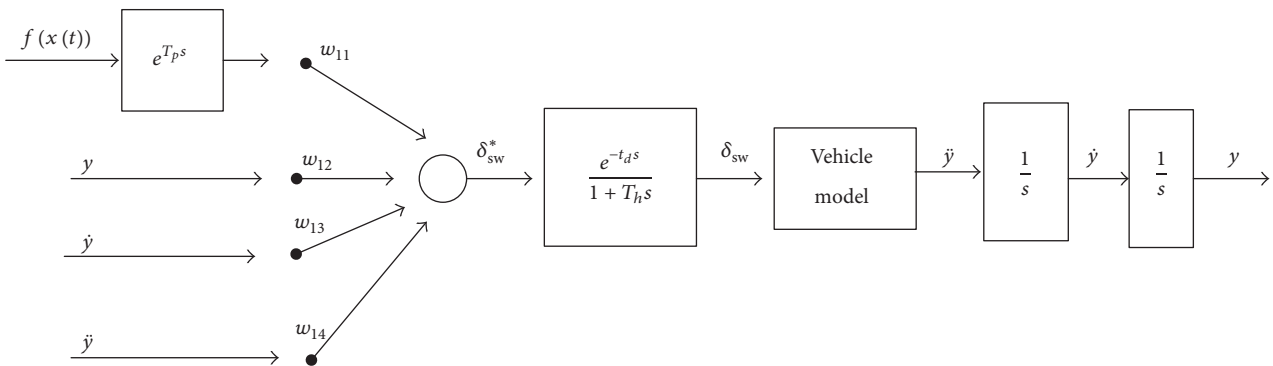


FIGURE 6: Driver model with state reference.



(a) The block diagram of vehicle model parameter identification



(b) The block diagram of driver model parameters identification

FIGURE 7: The diagram of cars' closed-loop system parameter identification.

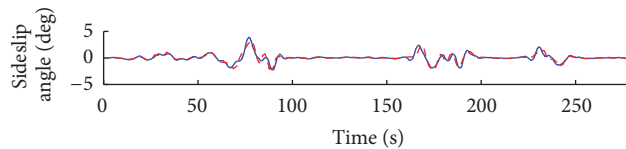
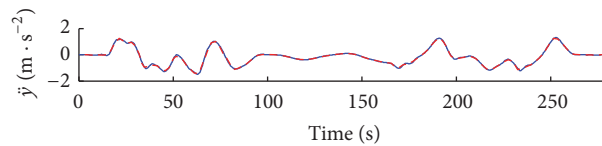
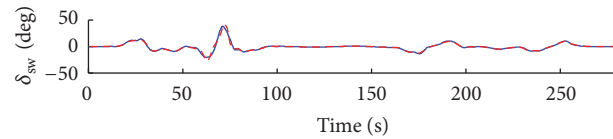
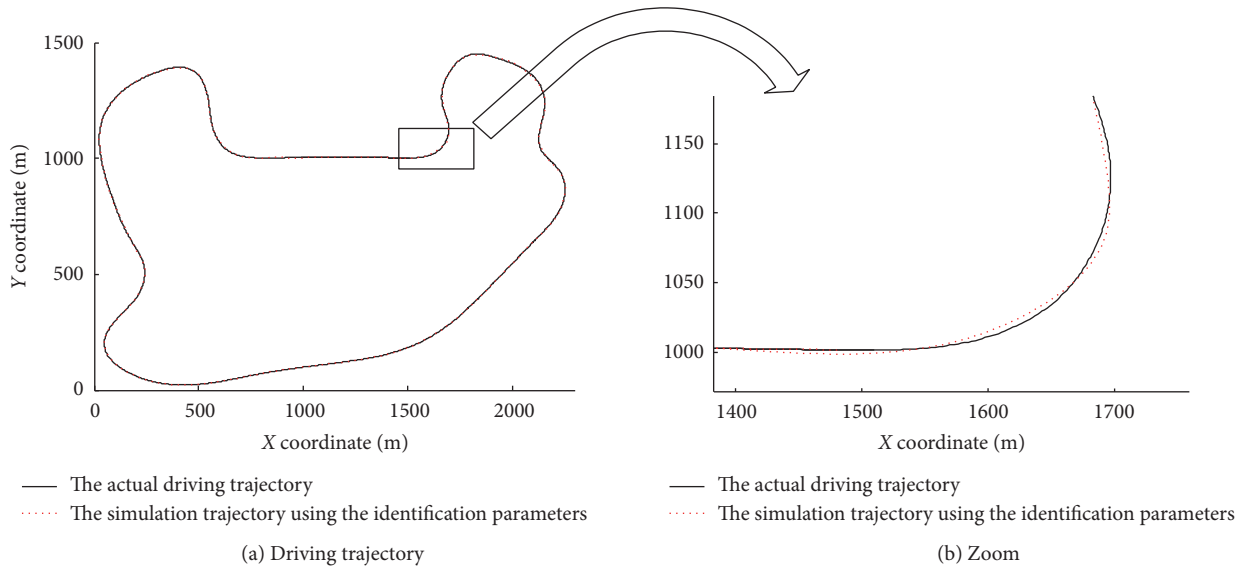


FIGURE 8: The contrast between normally driving theoretical data and actual data.

directional control model can simulate driving characteristics of emergency reaction when the driver's absence recovers.

Using formula (12) can solve probability  $A(t)$  of driver's attention being concentrated in continuous driving condition. According to formula (23), we can get distribution probability of attention in links of preview, judgment, and action in specific driving condition. Here we simulate the two conditions of changing lane and passing through right angle

intersection. Distribution of corresponding attention in each link is in Table 3.

According to formula (1), we can define variance of  $\sigma_{t_d}(t)$  and  $\sigma_{T_h}(t)$  of driver model parameters  $t_d(t), T_h(t)$ . Average nervous reaction time  $\bar{t}_d(t)$  and action reaction time  $\bar{T}_h(t)$  are direct microscopic description of driver's behavior. Research by Boom et al. shows mathematical characteristics of body fatigue can be described using Sigmoid function [19]. From

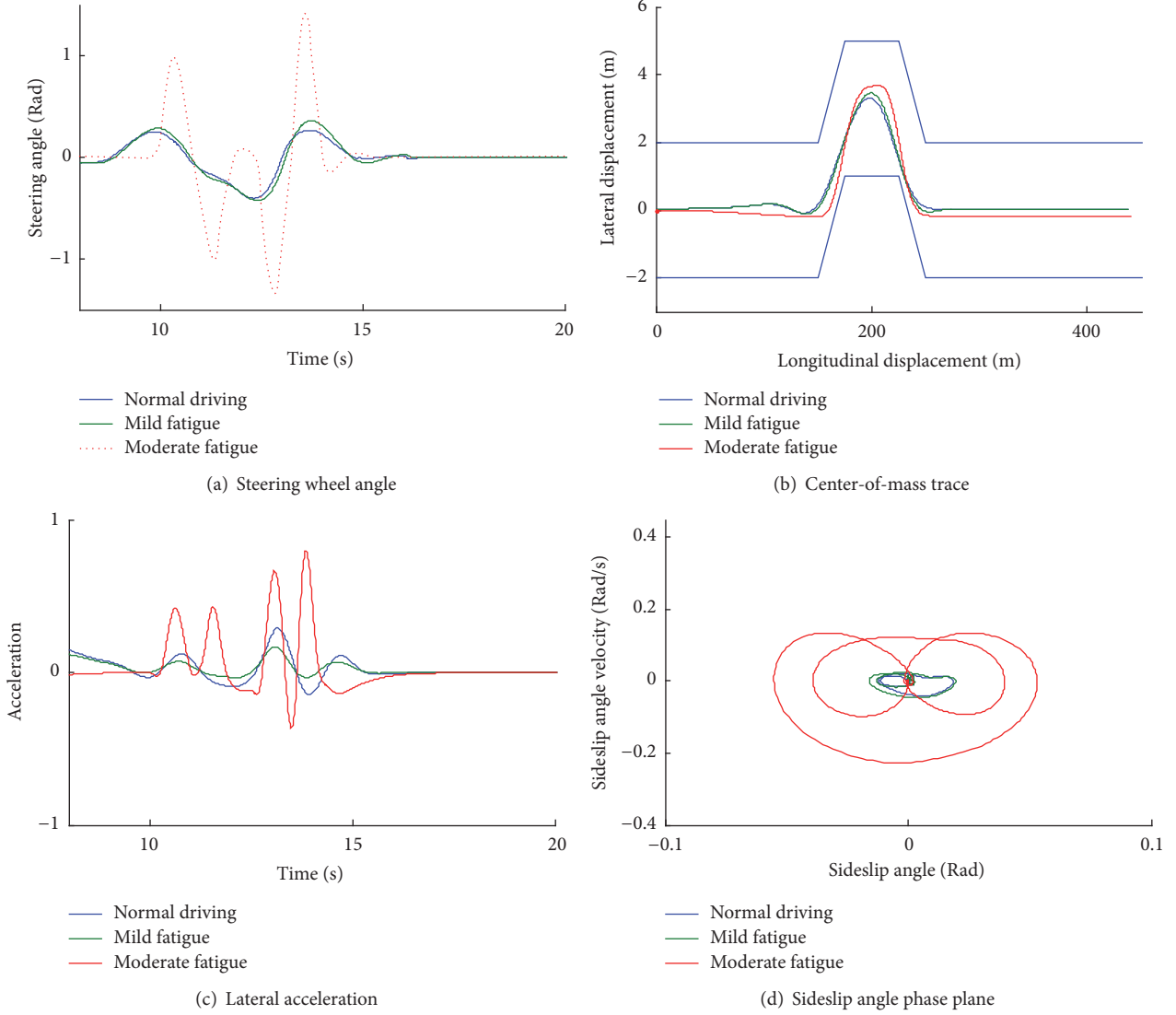


FIGURE 9: The simulation results of driver fatigue in double lane road.

this, we can deduce the relation between fatigue and average neuro and action reaction time:

$$\begin{aligned} \bar{t}_d &= \ln\left(-\frac{N_t - 1}{N_t}\right) \cdot \frac{(t_{da} - t_{db})}{4} + \frac{t_{da} + t_{db}}{2} \\ \bar{T}_h &= \ln\left(-\frac{N_t - 1}{N_t}\right) \cdot \frac{(T_{ha} - T_{hb})}{4} + \frac{T_{ha} + T_{hb}}{2}, \end{aligned} \quad (30)$$

where  $N_t$  is the driver's fatigue at time  $t$ ;  $t_{da}$  is the upper limit of driver's neuro reaction time;  $t_{db}$  is the lower limit of driver's neuro reaction time;  $T_{ha}$  is the upper limit of driver's action reaction time;  $T_{hb}$  is the lower limit of driver's action reaction time.

Important physical significance of this expression is that it presents the relation between fatigue index and average neuro and action reaction time. Then according to the relation between variance and attention of parameter distribution, we

can define probability distribution of driver model parameters in given fatigue index condition and get the relation between fatigue and driver model parameter.

To prove the correctness of fatigue driving behavioral model based on distraction model, we calculate and test the two types of common road conditions of changing lane and large curvature sharp cornering. Thereinto, changing lane is simulated using double lane change, and sharp cornering is substituted using  $90^\circ$  broken line. The auto model is subjected to calculation and simulation of closed-loop system of "driver-auto-road" using eight-degree-of-freedom model. According to the principle of guaranteeing safe conduct of auto, in selection of road width and car's speed, the selected road width  $B = 4$  m, and car speed  $u = 80 \text{ km}\cdot\text{h}^{-1}$  in simulation.

Figure 9 is simulation results for driver manipulating double lane change after continuous running of 2 hours (normal driving), 4 hours (slight fatigue), and 8 hours

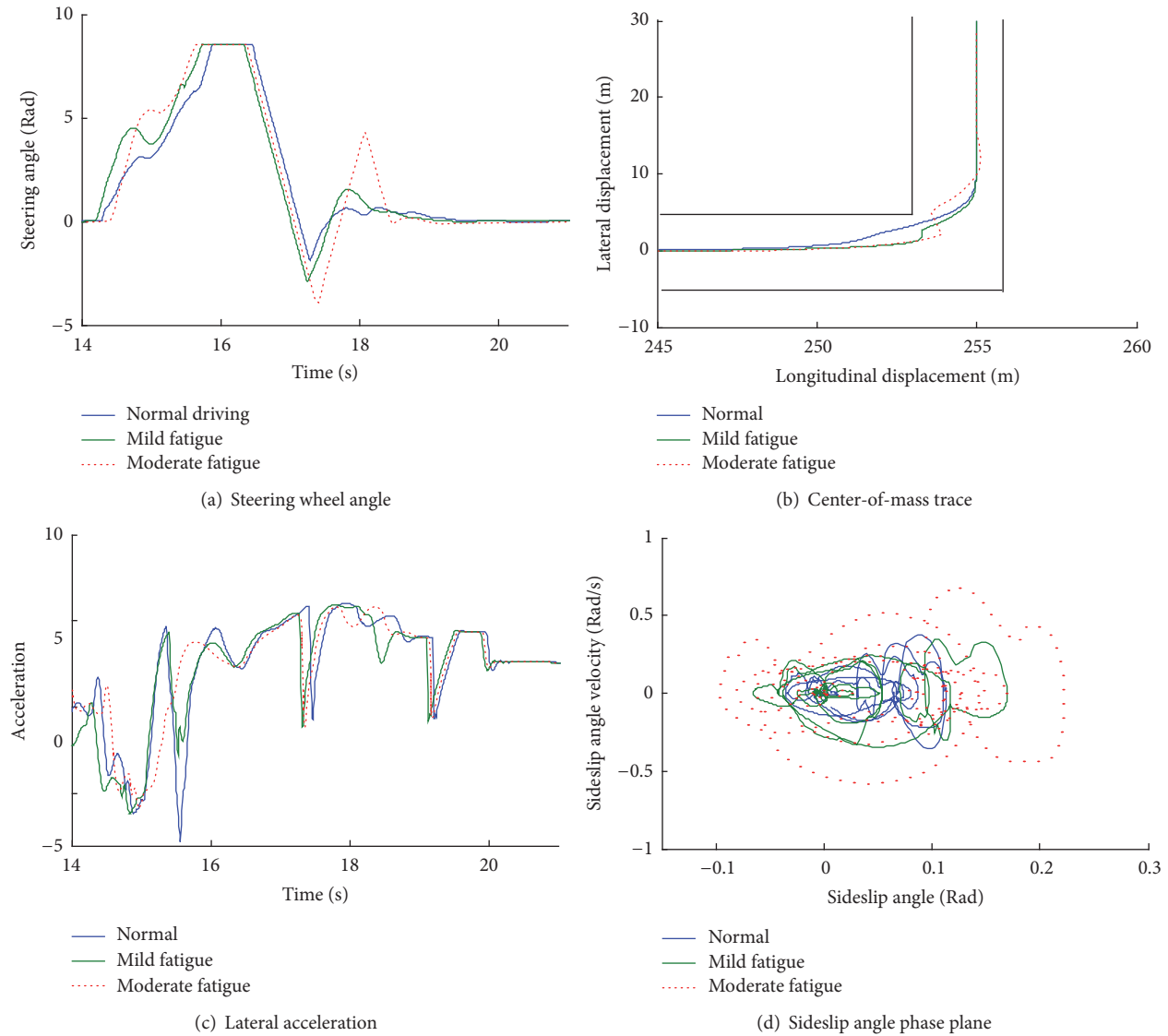


FIGURE 10: The simulation results of driver fatigue in right angles road.

(moderate fatigue), giving change curve representing turn angle of auto's steering wheel, mass center trajectory, lateral acceleration, and depression-depression speed phase plane.

From the figure we can see, with prolonging of continuous driving time, when the driver is in moderate fatigue state, the increase magnitude of steering wheel's operating frequency increases. This conclusion conforms to characteristics of steering wheel operation in driver's driving in fatigue state concluded by Shi et al. in Shanghai Jiaotong University by experiment [20]. The change trend of lateral acceleration is similar to turn angle of steering wheel, which obviously shows lateral stationarity of vehicle becomes bad.

Depression-depression speed phase plane is an index reflecting vehicle's stability margin [21]. The figure shows that, with prolonging of continuous driving time, closed region of phase plane becomes large, and vehicle's stability margin reduces. Simulation of road condition of double land change

shows, in condition of gentle variable camber, this model can conduct simulation experiment of vehicle's running state in fatigue driving.

Figure 10 is simulation result of right angle bent for continuous driving for 2 hours (normal driving), 4 hours (slight fatigue), and 8 hours (moderate fatigue). It shows that when turning a right angle, veteran drivers first turn steering wheel to left to turn the vehicle and then return to the normal state slowly. The operation is very steady. With prolonging of continuous driving time, magnitude of operating frequency of steering wheel increases due to slowness in closed-loop reaction, which is similar to the condition in simple road condition.

It is observed from depression-depression speed phase plane trajectory that vehicle's stability margin in condition of moderate fatigue reduces. Calculation result of right angle bent simulation indicates, on road with curvature suddenly

changing, the fatigue driving behavioral model based on distraction model can complete calculation simulation for vehicle's running state in fatigue state of driver.

## 7. Conclusion

Difference in vehicle's running environment will have a direct effect on driver's attention. To describe the characteristics of driver's attention changing with driving environment, establish the relation between driver model parameters and driver's attention, find the mapping relation between driver's behavior and vehicle's running status data, and provide simulation model for unmanned or auto controller, the paper established driver model based on driver's attention, with the following conclusions and contributions:

- (1) The paper researched shifting course of driver's attention from concentration to distraction and distribution characteristics of concentration duration and distraction duration of driver's attention and deduced the relation between attention concentration and continuous driving time according to conditional expectation formula.
- (2) It researched attention's random jump rule in the three links of preview, judgment, and action in the driving course and deduced state vector of attention's distribution in each link at specific time based on Markov process.
- (3) It obtained driver's attention index by measuring the time to open shield cover based on simulation of driving mask program and estimated the frequency by which the driver's attention concentration falls in time interval by frequency histogram and then got parameters of attention probability distribution density function.
- (4) The relationship between driver's mental state and manual closed-loop driving model parameters is established according to the shifting rule of attention in the driving course, and it is applied to driver model based on dynamical regulation neural network. Finally the paper researched dynamics evolution characteristics of vehicle running caused by fatigue driving in the environment of double lane change and large curvature.

## Competing Interests

The authors declare that they have no competing interests.

## Authors' Contributions

ShuanFeng Zhao and Wei Guo are equal contributors.

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