

Analysis and Synthesis of Driving Behavior based on Mode Segmentation

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Abstract: This paper presents the development of the modeling of human driving behavior based on an expression as a hybrid system (HS) focusing on the driver's vehicle following task. In our modeling, a relationship between the driver's sensory information and the output of driver is expressed by the piecewise ARX (PWARX) model, which is a class of the HS. As the sensory input, the range between vehicles, range rate, and time derivative of the area of the back of the preceding vehicle (called KdB) are considered. Also, the pedal operation is considered as the output. The identification problem for the PWARX model is solved using the clustering based technique. By introducing the PWARX model, it becomes possible to find not only parameters appearing in the operation in each mode but also parameters in the logical switching (decision making) conditions among them from the measured driving data. Furthermore, the obtained model is exploited for the design of assist system especially focusing on the switching condition of the ON/OFF of assist. The usefulness of the proposed assist system is confirmed by experiments.

Keywords: Driving behavior, Mode segmentation, Hybrid System.

1. INTRODUCTION

Recently, the demand for vehicle control systems is shifting from the realization of high performance vehicles to the development of safety and human-friendly vehicle control systems. One of the significant step to realize these demands is to analyze the human driving behavior and build the formal model of it.

Many ideas have been exploited for the driver modeling from viewpoint of control technology [1][2][3][4]. The common idea in these works is that the driver is regarded as a kind of "controller", and linear control theory has been applied to analyze the driving behavior. The linear controller model, however, may not work in the case that the driver is requested to operate the vehicle using not only simple reflexive motion but also higher level decision making. On the other hand, a nonlinear and/or stochastic modeling of human behavior such as neural networks (NN), hidden markov models (HMM) have been developed [5][6][7]. These techniques, however, have some problems as follows: (1) the obtained model often results in too complicated model, (2) this makes it impossible to understand the physical meaning of the driving behavior, and (3) the usefulness of information obtained by these models also remains questionable especially for the design of driving assist system based on the driver model.

When we look at the human behavior, it is often found that the driver appropriately switches the simple control laws instead of adopting the complex nonlinear control law [8][9][10]. This idea can be formally formulated by introducing a so-called "hybrid systems" (HS) wherein the switching among modes are represented by the discrete event-driven system while the dynamics of each mode is characterized by the continuous time-driven system. Furthermore, the switching mechanism can be regarded as a kind of driver's decision-making in the

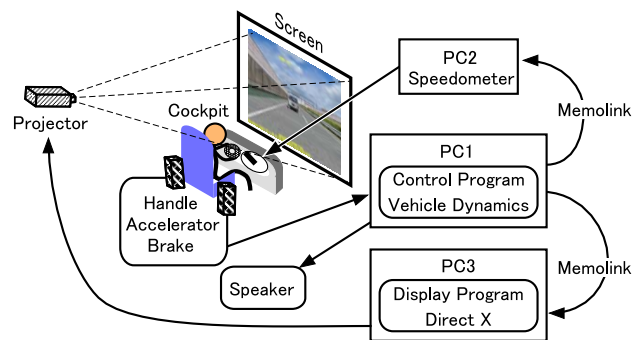


Fig. 1 Configuration of driving simulator (DS)

complex task. Thus, the introduction of the HS model leads to higher level understanding of the human behavior wherein the motion and decision making aspects are synthesized.

In this paper, first of all, the clustering based identification technique for the PWARX modeling [11] is introduced, and the long-term vehicle following task is analyzed. Second, a time derivative of the area of the back of the preceding vehicle projected on the driver's retina (called KdB [13]) is introduced as the sensory information (i.e. driver input) together with the range between vehicles and range rate. From the obtained PWARX model of human behavior, some interesting characteristics can be found. In particular, the KdB plays an important role in the decision making, i.e., the switching among modes. Finally, a design example of the assist system which utilizes the obtained model is described. The switching condition of the ON/OFF of assist is designed based on the identified hyperplane in the driver model. The usefulness of the proposed assist system is confirmed through experimental results.



Fig. 2 View from the driver

2. ACQUISITION OF DRIVING DATA

Configuration of the developed DS is shown in Fig.1. The display system provides the stereoscopic virtual environment. The display program was developed by exploiting the DirectX library. The cockpit is built by installing a seat, a handle, an accelerator, a brake, and a speedometer. The information on the driver output to the handle, accelerator, and brake is transferred to a PC1 through a USB terminal. Furthermore, the vehicle position and motion are calculated based on these inputs and vehicle dynamics implemented on the PC1 using the CarSim software. The results of the calculation are transferred to the PC2 and PC3 through the Memolink. The PC2 and PC3 control the speedometer, and the stereoscopic visual image based on the position and motion of the vehicle, respectively.

In this paper, we focus on the driver's vehicle following behavior on the expressway. The preceding vehicle runs with the velocity in the range of 0 to 130[km/h]. The weather is assumed to be sunny and the friction coefficient of the road was set to be 0.8. Drivers were provided with the instruction "Follow the preceding vehicle so as not to make collision". Since this instruction is "loose" instruction, the drivers do not concern much about the range and range rate. As the result, each driver can drive as his/her usual manner. The view from the driver is shown in Fig.2

3. MODELING OF THE VEHICLE FOLLOWING BEHAVIOR

3.1 Definition of driver input and output

In this subsection, driver input and output are defined. The driver input, i.e., the sensory information of the driver is defined as follows:

- Index for approaching (KdB) x_1
- Range between cars x_2
- Range rate between cars x_3

where KdB is an index which represents the logarithm of a time derivative of the area of the back of the preceding vehicle projected on the driver's retina as shown in Fig.3 [13]. In [13], it is verified that this index plays an important role in the vehicle following behavior from viewpoint of the cognitive science. The KdB can be expressed by using x_2 and x_3 as follows:

$$KdB = \begin{cases} -10 \times \log(|-2 \times \frac{x_3}{x_2} \times \frac{1}{5 \times 10^{-8}}|) & : x_3 > 0 \\ 10 \times \log(|-2 \times \frac{x_3}{x_2} \times \frac{1}{5 \times 10^{-8}}|) & : x_3 < 0 \end{cases} \quad (1)$$

Roughly speaking, the large KdB implies that the driver is facing dangerous situation. Note that KdB is set to be 0 when

$$-1 < -2 \times x_3 / (x_2^3 \times 5 \times 10^{-8}) < 1.$$

Also, the driver output is defined as follows:

- Pedal operation y

wherein the acceleration and braking operations are considered to take positive and negative values in y , respectively.

3.2 Representation as the PWARX model

We consider that there exist several modes in the driver's vehicle following behavior. In this subsection, the PWARX model is introduced as a mathematical model of the driving behavior because the PWARX model can express the input-output relation of the driving behavior by several ARX models. Furthermore, some identification techniques for the PWARX model have already been developed[11]

We consider the following PWARX model which has N modes:

$$y_{k+1} = \begin{cases} a_1 x_{1,k} + b_1 x_{2,k} + c_1 x_{3,k} + d_1 y_k & \text{if } \mathbf{x}_k \in C_1 \\ a_2 x_{1,k} + b_2 x_{2,k} + c_2 x_{3,k} + d_2 y_k & \text{if } \mathbf{x}_k \in C_2 \\ \vdots & \\ a_N x_{1,k} + b_N x_{2,k} + c_N x_{3,k} + d_N y_k & \text{if } \mathbf{x}_k \in C_N \end{cases} \quad (2)$$

where subscript k denotes the sampling index, and $\mathbf{x}_k = (x_{1,k}, x_{2,k}, x_{3,k})$. Also, C_1, \dots, C_N represent subspaces in the input data space. In this modeling, a_i, b_i, c_i and $d_i (i = 1, \dots, N)$ are unknown parameters. Furthermore, the boundaries between subspaces C_1, \dots, C_N are unknown. This point makes the identification problem

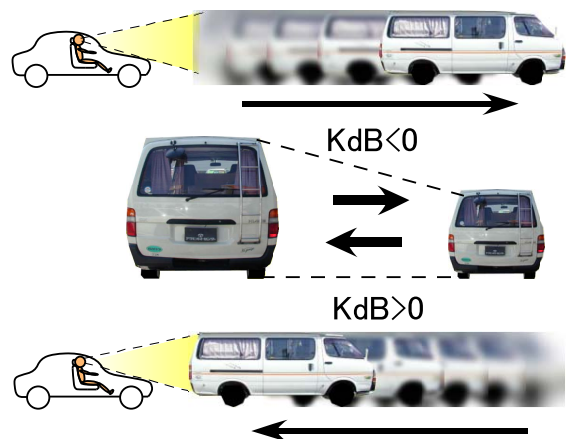


Fig. 3 Conceptual diagram of KdB

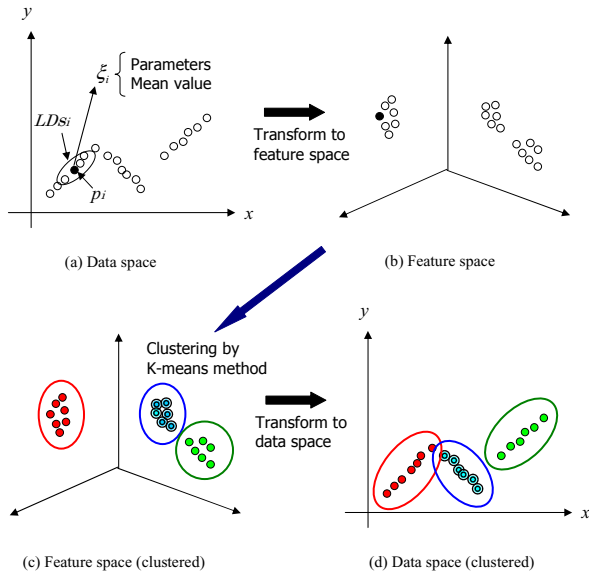


Fig. 4 Outline of the clustering

much more difficult than the standard parameter identification for the single ARX model. By introducing this PWARX model, it becomes possible to capture not only the operational aspect (represented by coefficients a_i , b_i and c_i ($i = 1, \dots, N$)) but also the decision making aspect (represented by boundaries between C_1, \dots, C_N) of the human behavior.

3.3 Mode classification by data clustering

In order to identify the parameters in the PWARX model, first of all, the input and output data are classified, and categorized into the corresponding modes. The outline of clustering is described as follows (See [11] in detail):

- Suppose that the sample data series $\{p_i\}$ ($i = 1, 2, \dots, n$) is given. For each sample data p_i ($i = 1, 2, \dots, n$), collect the neighboring c data, generate the data set LDs_i , and find the feature vector ξ_i (Fig.4(a)). Here, the feature vector ξ_i consists of the parameters calculated by applying the least mean square method together with the ARX model to the data in the LDs_i , and the mean value of the data in the LDs_i .
- Transform the series of sample data $\{p_i\}$ to the series of feature vectors $\{\xi_i\}$ ($i = 1, 2, \dots, n$) (Fig.4(b)). Apply the K-means algorithm to the $\{\xi_i\}$. (Fig.4(c)).
- Transform the clustering results in the feature vector space to one in the original sample data space (Fig.4(d)).

The parameters a_i , b_i , c_i and d_i ($i = 1, \dots, N$) are found by applying standard least mean square method to the sample data set in each mode defined by the clustering procedure.

After the mode classification, the switching hyperplanes between modes are identified using the support vector machine (SVM).

4. ANALYSIS OF THE VEHICLE FOLLOWING BEHAVIOR

We have analyzed the driving data of eleven male drivers (20s years old). The drivers tried to follow the preceding vehicle using their natural driving manner. The input and output data are sampled and collected every 240[msec]. All data are normalized before analysis.

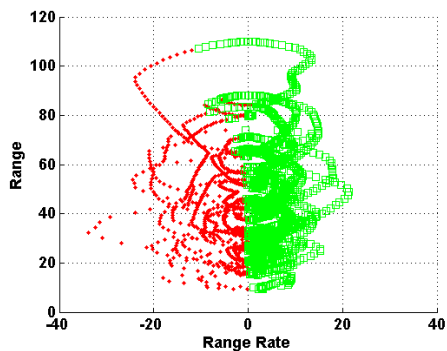
4.1 Number of modes and clustering results

Decision of the number of modes is a significant problem in the hybrid system identification. In Fig.5, the distribution of measured data of the driver A and results of mode classification in the cases of two-mode model and four-mode model are shown. These figures in Fig.5 are projected image of the original data space onto the space of range rate and range. For all eleven drivers, we could see the similar mode classification in the case that the number of modes is less than or equal to four. However, in the case that the number of modes is greater than four, there were lots of variations in the mode classification. Furthermore, the boundary between modes becomes unclear. This is considered to be caused by ‘over-segmentation’, and the meaning of each mode becomes somewhat obscure. Also, the least mean square errors are plotted for various number of modes in Fig.6(drivers A,B and C). From this figure, the four-mode model seems to be ‘semi-optimal’ model which takes a balance between the accuracy and the complexity. Based on these investigations, the number of modes is set to be four in the following analysis (denoted by mode A, B, C, and D).

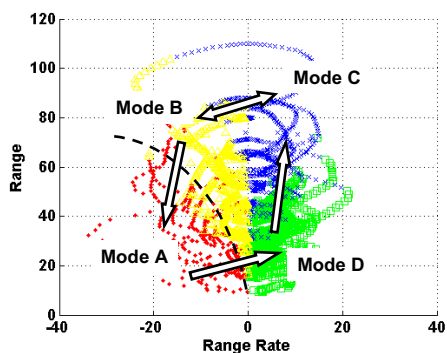
Figure7 shows the profiles of the measured data of the driver A. The horizontal axis represents the time, the vertical axes of the top, second, third, and bottom figures represent KdB, range, range rate, and pedal operation, respectively. The pedal operation takes positive value when the driver steps on the accelerator while takes negative value when the brake pedal is stepped on. In these profiles, results of the clustering (number of modes is four) are also indicated by different symbols. By observing this profile and mode classification, the typical mode transition is depicted in Fig.5(c). As stated below, since the mode A is the most significant mode from viewpoint of safety, the boundary of the mode A deserves to be analyzed. In Fig.5(c), the boundary of mode A is also indicated.

4.2 Identified parameters in the PWARX model (four modes)

The identified parameters of two drivers A and B in each mode are listed in Table 1. In the PWARX model, the parameter d represents the time constant of the human motion while the parameters a , b and c correspond to gains for the KdB, range and range rate, respectively. From the clustering results and identified parameters, the characteristics of each mode can be summarized as follows:



(a) two modes



(b) four modes

Fig. 5 Clustering with various number of modes (driver A)

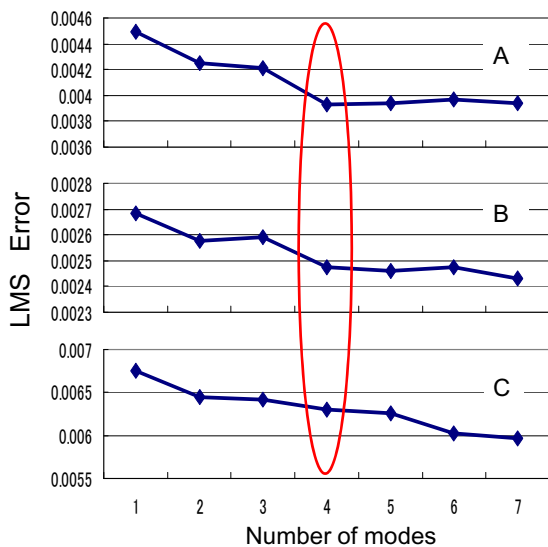


Fig. 6 LMS error for various number of modes (three drivers)

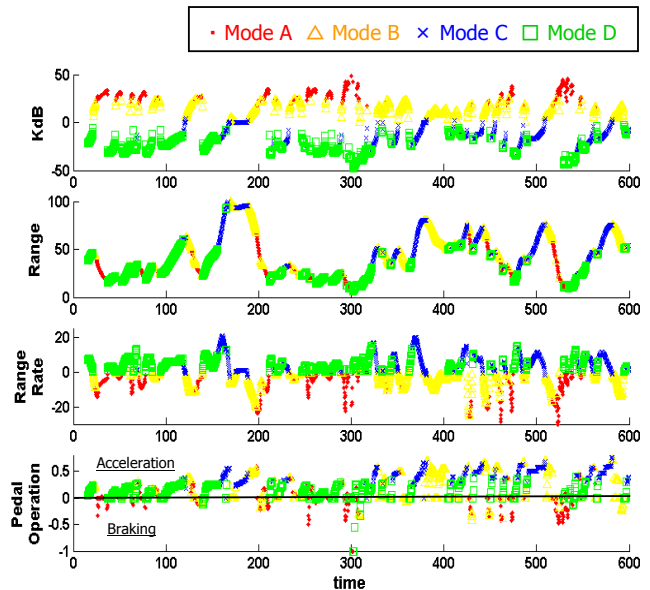


Fig. 7 Driving data profile (driver A, four modes)

Mode A (collision avoidance)

The mode A occupies the region of short range and negative range rate as shown in Fig.5(c). This implies that this mode takes the largest value of KdB among all modes. In other words, the mode A is the most dangerous mode in the vehicle following behavior. Furthermore, the parameter d takes smaller value compared with other modes (see Table 1). This implies that the drivers are forced to operate with fast dynamics in the mode A.

Mode B (approaching)

The mode B occupies the region of long range and negative range rate as shown in Fig.5(c). In this mode, the driver tries to approach the preceding vehicle. Furthermore, the parameter c takes larger value than other parameters (except d) in the mode. This implies that the drivers regard the range rate as important information in this mode.

Mode C (following control I: long range)

Table 1 Identified parameters in the PWARX model

subject	mode	a	b	c	d
A	mode A	-0.038	0.125	0.113	0.730
	mode B	-0.002	0.015	0.033	0.908
	mode C	0.027	0.021	0.085	0.940
	mode D	-0.015	-0.057	0.248	0.900
B	mode A	-0.060	0.295	0.223	0.769
	mode B	0.005	0.016	0.028	0.941
	mode C	-0.017	0.006	0.014	0.986
	mode D	-0.009	0.031	0.056	0.916

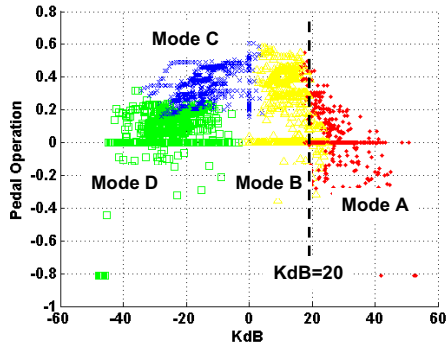


Fig. 8 Example of hyperplane between modes A and B (driver A)

The mode C occupies the region of long range and positive range rate as shown in Fig.5(c). This mode is the most safety mode during the overall vehicle following behavior.

mode D (following control II: short range)

The mode D occupies the region of short range and positive range rate as shown in Fig.5(c). This mode often appears after the mode A, i.e., collision avoidance mode.

4.3 Identification of switching hyperplanes (four modes)

Based on the clustering results, the switching hyperplanes are identified using the SVM. In this work, the hyperplanes are assumed to have the form

$$\alpha x_1 + \beta x_2 + \gamma x_3 = h. \tag{3}$$

The identified parameters in the switching hyperplanes of the drivers A and B are listed in Table 2. In Table 2, the hyperplanes I, II, and III separates the modes A and B, B and C, and C and D, respectively. The hyperplane IV separates the modes D and A. From the identified parameters, we can see that α , which is a coefficient of the KdB, takes the largest value among parameters except the hyperplane III of the driver B. This implies that the KdB plays an important role in mode transition. The data distribution in pedal-KdB space is shown in Fig.8 together with the hyperplane which separates the modes A and B.

Table 2 Identified parameters in the hyperplane

subject	plane	α	β	γ	h
A	I	5.570	-2.734	-3.548	2.030
	II	4.559	-2.642	-2.544	-0.227
	III	6.472	5.759	-1.166	0.275
	IV	3.381	0.600	-0.569	0.248
B	I	5.744	-3.689	-3.129	1.593
	II	3.502	-1.740	-1.421	-0.149
	III	3.110	3.542	2.430	0.873
	IV	3.425	-0.463	-0.923	0.143

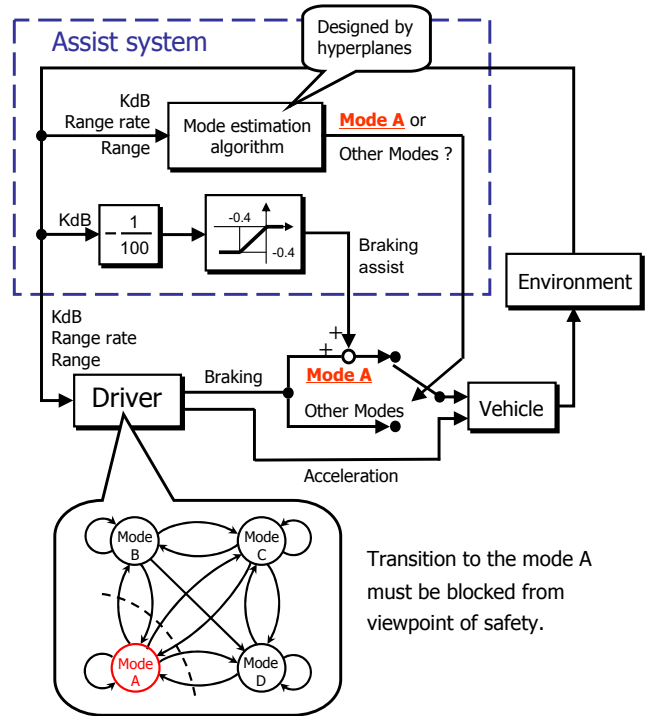


Fig. 9 Braking assist system based on driver’s HS model

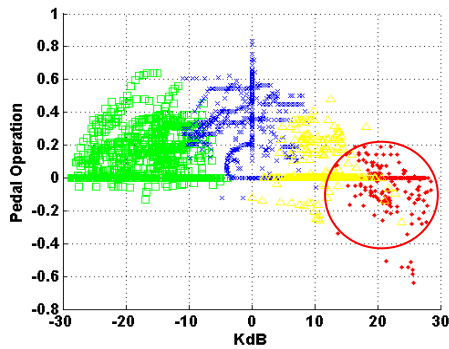
5. APPLICATION TO ASSIST SYSTEM DESIGN

The HS model plays an essential role to design an assist system for safety. From viewpoint of safety, it is important to reduce the sojourn time in the mode A. Therefore, the assist system must be designed so as to avoid the mode A. The blockdiagram of the proposed assist controller together with the driver, vehicle and environment is depicted in Fig.9. In Fig.9, the braking assist controller is embedded. The switching condition between assist and no-assist modes in the controller is designed by the identified switching hyperplane between mode A and other modes of the driver. This implies that the implemented switching condition varies from driver to driver. As the assist operation, the assist braking is calculated by $-x_1 \times 0.01$ (with saturation), and is added to the driver’s braking operation. Note that this assist is activated only while the driver is in the mode A and does not step on the accelerator.

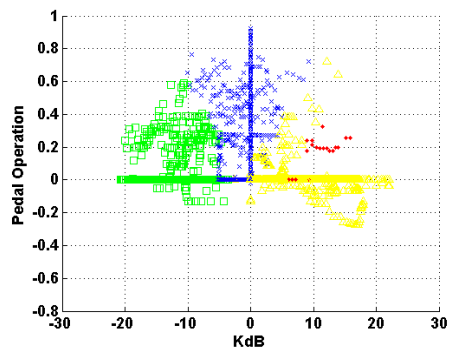
In order to verify effect of the assist, the data distribution of driver C in the cases of with and without assist are shown in Fig.10. We can see that the number of data which belong to the mode A is drastically reduced thanks to the effect of the assist as indicated by the red circle.

6. CONCLUSIONS

This paper has presented the development of the modeling of human driving behavior based on an expression as the PWARX model focusing on the driver’s vehicle following task. As the sensory input, the range between vehicles, range rate, and time derivative of the area of the back of the preceding vehicle (called KdB) were consid-



(a) without assist (driver C)



(b) with assist (driver C)

Fig. 10 Effect of assist (driver C)

ered. Also, the pedal operation was considered as the output. The identification problem for the PWARX model was solved using the combination of the data clustering and support vector machine. By introducing the PWARX model, it became possible to find not only parameters appearing in the operation in each mode but also parameters in the logical switching (decision making) conditions between them from the measured driving data. From the obtained results, it has been found that the driver appropriately switches some “control laws” according to the sensory information, in particular, the KdB plays an important role in the decision making, i.e., the switching between modes. Finally, the driver model was exploited for the design of assist system especially focusing on the switching condition of the ON/OFF of assist. The usefulness of the proposed assist system was confirmed by experiments.

Our future works are listed below:

- More sophisticated design of the assist system which can optimize some performance index for the driver-vehicle system.
- Higher level understanding of the human behavior based on the investigation of identified parameters in the HS model.
- Application to more complex task.

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