Model Predictive Assisting Control of Vehicle Following Task Based on Driver Model

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Abstract—A personalized driver assisting system that makes use of the driver’s behavior model is developed. As a model of driving behavior, the Probability-weighted ARX (PrARX) model, a type of hybrid dynamical system models, is introduced. A PrARX model that describes the driver’s vehicle-following skill on expressways is identified using a simple gradient descent algorithm from actual driving data collected on a driving simulator. The obtained PrARX model describes the driver’s logical decision making as well as continuous maneuver in a uniform manner. Finally, the optimization of the braking assist is formulated as a mixed-integer linear programming (MILP) problem using the identified driver model, and computed online in the model predictive control framework.

I. INTRODUCTION

In recent years, personalized driver assisting system has been attracting growing attention as a key-technology for realizing a reliable automobile. In order to develop a driver assisting system that can meet each specific customer’s requirements, a mathematical model that is capable of capturing complex driving skills is needed. The use of conventional system identification techniques, such as nonlinear regression models, neural networks (NNs), and fuzzy systems (for example, [1]), poses certain problems; 1) the obtained model is often too complicated, and 2) this, in turn, makes it difficult to interpret the model parameters. When we observe driving behavior, it is often found that a driver realizes a complex maneuver by switching between multiple primitive skills instead of adopting a single complex nonlinear control law. This switching can be attributed to the driver’s decision-making process, and this consideration strongly motivates us to model human driving behavior as a hybrid dynamical system (HDS). HDSs comprise both continuous dynamics and discrete mode changes. The former are typically expressed by differential (or difference) equations and the latter are expressed by automata, logic, etc. By regarding the driver’s primitive skills and switching rules as the continuous and discrete parts of an HDS, respectively, the understanding of the human driving behavior can be recast as a parameter estimation problem in the HDS framework. Therefore, introduction of the hybrid system model leads to an understanding of the human behavior wherein the motion control and the decision making functions are synthesized. This is the significant advantage over the conventional control-oriented driver models [2][3][4][5].

The main concern in the hybrid system identification is how to identify the parameters in the continuous dynamics and those which specify the discrete switching conditions. One of the most widely accepted hybrid system identification methods is the ones based on the Piece-Wise affine AutoRegressive eXogeneous (PWAX) models [6][7][8][9][10][11][12]. In [13], the PWAX is applied to the analysis of driving behavior. However, most of the identification algorithms developed so far often require huge computational cost. Moreover, the application of the HDS model to the analysis of human behavior has not yet been fully discussed. In [14], the authors have proposed a system identification method based on the Probability-weighted ARX (PrARX) model and analyzed the driving behavior. Unlike the PWAX model, the PrARX model uses ‘softmax’ functions in the expression of discrete switching. Thanks to the smoothness of the softmax function, the parameter estimation for the PrARX model is formulated as a single optimization problem, which can be efficiently computed by gradient-based techniques. In addition, the identified PrARX model can be transformed into a PWAX model in a systematic manner.

Based on the previous result, in this paper, we develop a driver assisting control system, which makes use of the PrARX model of the driving behavior and computes optimal assists under the framework of model predictive control (MPC). More precisely, we consider braking assist control for the vehicle-following task on expressways. First, the driver’s behavior model is identified from driving data collected using a driving simulator (DS). The identified PrARX model is then transformed into a PWAX model. Finally, the optimization of braking assist is formulated as a mixed-integer linear programming (MILP) problem based on the MLD+MILP framework developed in [15]. The proposed assisting control system computes the assisting braking amount by solving MILP online in the MPC control loop.

This paper is organized as follows: In Section II, a virtual driving environment developed in this study is described. The PrARX model and its identification method is reviewed in Section III. In Section IV, the vehicle-following skill is modeled and analyzed. In Section V, the proposed model predictive assisting control is described and experimental results are shown. Finally, concluding remarks are given in Section VI.

II. ARCHITECTURE OF DRIVER ASSISTING SYSTEM

Fig. 1 shows the overall architecture of the proposed driver assisting system. In this paper, we consider the vehicle-
following behavior on expressways. The driving environment is realized by a driving simulator. The view from the driver is shown in Fig. 2. The examinee’s driving operation is measured by encoders attached to the steering wheel, the accelerator, and the brake, placed in front of the driver’s seat. The measured data are input to the driving simulator to compute the physical behavior of the vehicles (the examinee’s car and the leading car) based on precise mathematical models. At the same time, the data are collected to be used for the offline identification of the examinee’s driving behavioral model, as described in Section IV. The visual image of the virtual environment is projected onto a wide screen in front of the driver. Driving sound is displayed from the speakers. The assisting controller receives physical information from the driving environment and generates assisting brake based on model predictive control (MPC). In MPC, the examinee’s behavioral model and simplified vehicle models are used. At every control cycle, an optimal assisting brake sequence is obtained by solving a mixed-integer linear programming (MILP) problem, and the first element of the sequence is superimposed on the examinee’s brake operation. See Section (MILP) problem, and the first element of the sequence is obtained by solving a mixed-integer linear programming (MPC). In MPC, the examinee’s behavior is predicted based on the driving environment and generated assisting brake. The upper figure shows the three ARX models (dashed line) and the PrARX model (solid line), which is given by

\[ y_k = f_{Pr}(\varphi_k) + e_k \]  

(1)

where \( k \geq 0 \) denotes the sampling index, \( y_k \in \mathbb{R}^q \) is the output variable and \( e_k \) is an error term. The symbol \( \varphi_k \in \mathbb{R}^{n+1} \) denotes an augmented regressor vector defined by

\[ \varphi_k = [y_{k-1}^T \cdots y_{k-n_a}^T u_{k-1}^T \cdots u_{k-n_b}^T]^T \]  

(2)

where \( n = p \cdot n_a + q \cdot n_b \) and \( u_k \in \mathbb{R}^p \) is the input variable. In a special case where \( n_a = 0 \), \( \varphi_k \) is defined as

\[ \varphi_k = [u_{k-1}^T \cdots u_{k-n_b}^T]^T. \]

\( f_{Pr}(\varphi_k) \) is a function of the form

\[ f_{Pr}(\varphi_k) = \sum_{i=1}^{s} P_i(\varphi_k)\theta_i^T \varphi_k. \]  

(3)

\( \theta_i \in \mathbb{R}^{(n+1) \times q} \) \( (i = 1, \ldots, s) \) is an unknown parameter matrix of each mode, where \( s \) denotes the number of modes. \( P_i(\varphi_k) \) denotes the probability that the augmented regressor vector \( \varphi_k \) belongs to Mode \( i \), and is given by the softmax function as follows:

\[ P_i(\varphi_k) = \frac{\exp (\eta_i^T \varphi_k)}{\sum_{j=1}^{s} \exp (\eta_j^T \varphi_k)}, \]

\[ \eta_i = 0 \]  

where \( \eta_i \) \( (i = 1, \ldots, s - 1) \) is an unknown parameter that characterizes the probabilistic partition of the augmented regressor space.

A simple example is shown in Fig. 3. This model is a single-input-single-output PrARX model with 3 modes. The parameters \( n_a \) and \( n_b \) are set as 0 and 1, respectively. The model parameters are given by

\[ \theta_1 = [0.5 \ -5]^T, \quad \theta_2 = [-0.1 \ 3]^T, \]

\[ \theta_3 = [-0.4 \ 15]^T, \]

\[ \eta_1 = [-3 \ 45]^T, \quad \eta_2 = [-1.5 \ 30]^T, \]

\[ \eta_3 = [0 \ 0]^T. \]  

(5)

The upper figure shows the three ARX models (dashed line) and the PrARX model (solid line), which is given by the weighted composition of the three ARX models. The lower figure shows the three softmax functions used as the weighting probabilities in the PrARX model. It can be seen that the ARX models are smoothly connected around \( u = 10 \) and \( 20 \). These connecting points, i.e., the partitions can be calculated from \( \eta_1 \) and \( \eta_2 \) (See III-C).

B. Identification Algorithm

In order to identify the parameters in a PrARX model, the steepest descent method is used. A cost function is defined as the square norm of the output error as follows:

\[ \epsilon = \frac{1}{N} \sum_{k=1}^{N} \|e_k\|^2 = \frac{1}{N} \sum_{k=1}^{N} \|y_k - f_{Pr}(\varphi_k)\|^2 \]  

(6)
Remark 1 The parameters $\theta_i$ in the ARX models and $\eta_i$ in the partitions of the regions (softmax function) can be optimized simultaneously in a single optimization, thanks to the continuity of the softmax function. This is a remarkable advantage of the PrARX model to the PWARX model, for which $\theta_i$ and $\eta_i$ are often identified separately.

Remark 2 Since the steepest descent method may result in local minima, sufficiently many initial parameters must be tested to find the globally optimal parameters.

C. Transformation to PWARX model

A PWARX model is defined by the form

$$y_k = f_{PW}(\phi_k) + \epsilon_k.$$  

$f_{PW}(\phi_k)$ is a piecewise affine (PWA) function of the form

$$f_{PW}(\phi_k) = \begin{cases} 
\theta_1^{(t)} \phi_k & \text{if } \phi_k \in R_1 \\
\vdots & \vdots \\
\theta_s^{(t)} \phi_k & \text{if } \phi_k \in R_s
\end{cases}$$

where $\{R_i\}_{i=1}^{s}$ gives a complete partition of the regressor domain. Each region $R_i$ is a convex polyhedron described by

$$R_i = \{ \phi \in \mathbb{R}^{n+1} : H_i \phi \preceq [0] \}$$

where $H_i$ is a matrix which defines the polyhedron $R_i$. The symbol $\preceq$ denotes a vector, each of whose elements is either $\leq$ or $<$, determined so as to make $\{R_i\}_{i=1}^{s}$ a partition.

Now, consider converting a PrARX model into a PWARX model. Suppose that $\eta_i \neq \eta_j$ ($\forall i, j; i \neq j$) holds. We assign each $\phi_k$ to a mode using the following rule:

$$\phi_k \in R_i \quad i = \text{arg max}_{i=1,...,s} P_i(\phi_k).$$

For some $\phi_k$, there may be more than one mode having the maximum and equal probabilities. If this is the case, it is assigned to the mode with the largest index. This mode assignment implies that the $R_i$ is represented by using $\eta_i$s as follows:

$$R_i = \{ \phi \in \mathbb{R}^{n+1} : \eta_1 \phi \leq \eta_i \phi, \ldots, \eta_i-1 \phi \leq \eta_i \phi, \eta_i+1 \phi < \eta_i \phi, \ldots, \eta_s \phi < \eta_i \phi \}.$$  

Alternatively, $R_i$ is written as

$$R_i = \{ e \in \mathbb{R}^n : H_i e \preceq [i] \},$$

$$H_i = [(\eta_1 - \eta_i) \cdots (\eta_s - \eta_i)]^T$$

where the $j$-th element of $\preceq [i]$ is ‘$\leq$’ if $j < i$ and ‘$<$’ otherwise. We can confirm that $\{R_i\}_{i=1}^{s}$ defines a complete partition of the regressor space (a proof is given in [14]). In this way, a PrARX model can be directly transformed into a PWARX model.

IV. DRIVING BEHAVIOR ANALYSIS USING PRARX MODELS

In this section, the PrARX model is applied to the analysis of the driving behavioral data, and the usefulness is verified.

A. Acquisition of Driving Data

As previously mentioned, we focus on the drivers’ vehicle-following behavior on expressways. The velocity of the leading vehicle varies from 0 to 130 [km/h]. The term range refers to the relative distance between the driver’s vehicle and the leading vehicle, and the term range rate refers to the time derivative of the range. All drivers are provided with the instruction “Follow the leading vehicle so as not to make a collision”. Due to this ‘loose’ instruction, the drivers are provided with no prior knowledge about desired range and range rate. The intention is to let the drivers drive in his/her usual manner.

B. Definition of Driver Input and Output

The driver is regarded as a kind of controller to follow the leading vehicle. In this subsection, the driver inputs and outputs are defined. The driver input $u_k = [u_{1,k} \ u_{2,k} \ u_{3,k}]^T$, i.e., the sensory information of the driver is defined as follows:

- Risk feeling index (KdB) : $u_{1,k}$
• Range between cars : $u_{2,k}$
• Range rate between cars : $u_{3,k}$

Here, KdB is a risk-feeling index, obtained by taking the logarithm to the time derivative of the back area of the leading vehicle projected onto the driver’s retina [16]. In [16], it is verified that this index plays an important role in the vehicle following behavior from the viewpoint of cognitive science. The KdB can be expressed by using $u_2$ and $u_3$ as follows:

$$ u_1 = \begin{cases} 
-10 \times \log | -2 \times \frac{u_2}{w_2} \times \frac{1}{5 \times 10^{-7}} | & \text{if } u_3 > 0 \\
10 \times \log | -2 \times \frac{u_2}{w_2} \times \frac{1}{5 \times 10^{-7}} | & \text{if } u_3 < 0 
\end{cases} \quad (18) $$

Intuitively speaking, the large KdB implies that the driver is facing a dangerous situation. The driver output is defined as follows:

• Pedal operation : $y_k$

Here, the acceleration and braking operations are considered to take positive and negative values in $y_i$, respectively. Since we consider a first-order dynamics as the controller model, the regressor vector $\varphi_k$ is defined as follows:

$$ \varphi_k = [y_{k-1} \ u_{1,k-1} \ u_{2,k-1} \ u_{3,k-1}]^T. \quad (19) $$

All observed data are normalized before identification.

C. Modeling Results

We have analyzed the driving data of two male drivers, both 20s years old. Each driver model is identified from 2434 points of data, sampled and collected every 200 milliseconds.

1) Mode Estimation Results: The mode estimation results in the case of two-mode modeling of the drivers A and B are shown in Fig. 4 and Fig. 5, respectively. In these figures, data points are plotted in the Range rate - Range space. The color of each data point is determined by blending red and blue reflecting the mode probabilities; if $P_1 = 1$, the point is depicted red, and if $P_2 = 1$, the point is depicted blue. We observe that in Mode 1 (the mode depicted red), the range is relatively small and the range rate is relatively large in the negative direction compared to Mode 2. This implies that the driver has switched the internal driving skill after recognizing the danger of collision. Therefore, from now on, we call Mode 1 the dangerous mode.

2) Identified Parameters: The identified parameters in the PrARX model for Driver A are shown in Table I.

<table>
<thead>
<tr>
<th>Mode (i)</th>
<th>$\theta_{i1}$</th>
<th>$\theta_{i2}$</th>
<th>$\theta_{i3}$</th>
<th>$\theta_{i4}$</th>
<th>$\theta_{i5}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.488</td>
<td>-0.282</td>
<td>0.016</td>
<td>0.104</td>
<td>0.180</td>
</tr>
<tr>
<td>2</td>
<td>0.311</td>
<td>-0.006</td>
<td>0.056</td>
<td>0.008</td>
<td>-0.014</td>
</tr>
<tr>
<td>$\eta_1$</td>
<td>$\eta_{11}$</td>
<td>$\eta_{12}$</td>
<td>$\eta_{13}$</td>
<td>$\eta_{14}$</td>
<td>$\eta_{15}$</td>
</tr>
<tr>
<td>1</td>
<td>-13.385</td>
<td>4.404</td>
<td>0.108</td>
<td>-7.800</td>
<td>-4.327</td>
</tr>
</tbody>
</table>

It is observed that the parameter $\theta_{i2}$ and $\theta_{i4}$ tend to be larger in Mode 1 than in Mode 2. This implies that Driver A uses higher feedback gains for the risk feeling index KdB and for the range-rate in Mode 1. On the other hand, the probability that a point belongs to each mode can be calculated from $\eta_1$ and $\eta_2$. The matrices $H_1$ and $H_2$, which specify the mode regions of the corresponding PWARX model, are given by

$$ H_1 = \begin{bmatrix} \eta_1 - \eta_1 \\ \eta_2 - \eta_1 \end{bmatrix} = \begin{bmatrix} 0 \\ -\eta_1 \end{bmatrix}, \quad (20) $$

$$ H_2 = \begin{bmatrix} \eta_1 - \eta_2 \\ \eta_2 - \eta_2 \end{bmatrix} = \begin{bmatrix} \eta_1 \\ 0 \end{bmatrix}. \quad (21) $$

The partition between Mode 1 and Mode 2 is given by

$$ \eta_1^T \varphi_k = 0. \quad (22) $$

Therefore, the large element in the $\eta_1$ represents that it strongly affects on the partition between modes, i.e., the driver’s decision making. In Table I, it can be seen that the KdB and the range rate have strong influence on the decision making for Driver A. Generally speaking, the KdB has strong influence on the decision making. The parameter $\eta_1$ can be an important feature value to design the assisting system which accommodates with each driver’s personality.

V. MODEL PREDICTIVE ASSISTING SYSTEM DESIGN

In this section, we design a model predictive assisting controller which prevents the driver from facing a dangerous
In addition, the introduction of the auxiliary variables \( z \) of the leading vehicle is calculated based on a simple linear assisting output, the information on the leading vehicle as operation. The longitudinal direction is expressed as follows:

\[
\begin{align*}
y_k &= \theta_1^T \varphi_k \quad \text{if } \eta_1 \varphi_k > 0, \\
y_k &= \theta_2^T \varphi_k \quad \text{if } \eta_1 \varphi_k \leq 0.
\end{align*}
\]  

(23)

This PWARX model can be transformed to a linear model with inequalities and integer constraints by applying same idea used in the derivation of the MLDS description. A brief summary is described in the following. First, a binary variable \( \delta_{1,k} \) is introduced:

\[
[\delta_{1,k} = 1] \iff [\eta_1 \varphi_k > 0].
\]  

(24)

This equivalence relation can be transformed to the following inequalities.

\[
\begin{align*}
\eta_1 \varphi_k &\leq M_1 \cdot \delta_{1,k}, \\
\eta_1 \varphi_k &\geq \epsilon + (m_1 - \epsilon) \cdot (1 - \delta_{1,k})
\end{align*}
\]  

(25)

where \( M_1 \) and \( m_1 \) denote the maximum and minimum values of \( \eta_1 \varphi_k \), respectively, and \( \epsilon \) denotes a small positive constant. In addition, the introduction of the auxiliary variables \( z_{1,k} = \delta_{1,k} \varphi_k, z_{2,k} = (1 - \delta_{1,k}) \varphi_k \) leads to

\[
y_k = \theta_1^T z_{1,k} + \theta_2^T z_{2,k}.
\]  

(26)

Now, we consider the following assisted driver model.

\[
\begin{align*}
y_{total,k} &= \theta_1^T z_{1,k} + \theta_2^T z_{2,k} + z_{as,k} \\
z_{as,k} &= y_{as,k} \delta_{1,k}
\end{align*}
\]  

(27)

where \( y_{as,k} \) denotes the assisting output. Equation (27) implies that the assisting output is superimposed on the driver’s output only when the driving mode is Mode 1 (the dangerous mode). On the other hand, a simplified vehicle dynamics in the longitudinal direction is expressed as follows:

\[
\begin{align*}
v_{o,k} &= v_{o,k-1} + y_{total,k-1} \cdot y_{max} \cdot T \\
p_{o,k} &= p_{o,k-1} + v_{o,k-1} \cdot T
\end{align*}
\]  

(28)

where \( v_{o,k} \) and \( p_{o,k} \) denote the velocity and position of the examinee’s vehicle, respectively, and \( T \) denotes the sampling period. \( y_{max} \) is a normalization coefficient for the pedal operation.

In order to formulate the optimization problem for the assisting output, the information on the leading vehicle as well as input variables must be predicted. Here, the behavior of the leading vehicle is calculated based on a simple linear prediction:

\[
\begin{align*}
p_{f,k} &= p_{f,k-1} + v_{f,k-1} \cdot T \\
v_{f,k} &= v_{f,k-1}
\end{align*}
\]  

(29)

where \( p_{f,k} \) and \( v_{f,k} \) are position and velocity of the leading vehicle. The prediction of the range and range rate are calculated as follows:

\[
\begin{align*}
u_{2,k} &= (p_{f,k} - p_{o,k}) / d_{max}, \\
u_{3,k} &= (v_{f,k} - v_{o,k}) / v_{max}.
\end{align*}
\]  

(30)

Here, \( d_{max} \) and \( v_{max} \) are normalization coefficients for the range and range rate. In addition, the variable \( u_{1,k} \) (the KdB) is a nonlinear function of \( u_{2,k} \) and \( u_{3,k} \) as shown in (18), and it is approximated by the following piecewise affine function:

\[
\begin{align*}
u_{1,k} &= \alpha_1 u_{2,k} + \alpha_2 u_{3,k} + \alpha_3 \quad \text{if } u_{3,k} > 0 \\
u_{1,k} &= \beta_1 u_{2,k} + \beta_2 u_{3,k} + \beta_3 \quad \text{if } u_{3,k} \leq 0
\end{align*}
\]  

(31)

Again, the binary variable \( \delta_{2,k} \) is introduced to obtain the equivalent linear inequalities:

\[
[\delta_{2,k} = 1] \iff [u_{3,k} > 0],
\]  

(32)

and this equivalence relation is transformed to the following inequalities:

\[
\begin{align*}
u_{3,k} &\leq M_2 \cdot \delta_{2,k}, \\
u_{3,k} &\geq \epsilon + (m_2 - \epsilon) \cdot (1 - \delta_{2,k})
\end{align*}
\]  

(33)

where \( M_2 \) and \( m_2 \) denote the maximum and minimum values of \( u_{3,k} \), respectively. Introduction of the auxiliary variables \( z_{3,k} = \delta_{2,k} u_{2,k}, z_{4,k} = \delta_{2,k} u_{3,k}, z_{5,k} = (1 - \delta_{2,k}) u_{2,k}, z_{6,k} = (1 - \delta_{2,k}) u_{3,k} \) leads to

\[
u_{1,k} = \alpha_1 z_{3,k} + \alpha_2 z_{4,k} + \alpha_3 + \beta_1 z_{5,k} + \beta_2 z_{6,k} + \beta_3.
\]  

(34)

Finally, the objective of the assisting control is specified by the reduction of the risk feeling index in Mode 1 given by

\[
z_{risk,k} = \delta_{1,k} u_{1,k}.
\]  

(35)

The auxiliary variables \( z_{as,k} \) in (27) and \( z_{risk,k} \) in (35), which are products of a binary variable and a continuous variable, can be converted to equivalent linear inequalities. As a result, the optimization for the assisting output is formulated as a mixed-integer linear programming (MILP) problem as shown below.

**Optimization of assisting control**

Given:

\[
u_{1,1}, u_{2,1}, u_{3,1}, y_{total,1}, v_{f,k}, p_{f,k} \quad (k \in \{1, 2, \cdots, K\})
\]  

(36)

Find:

\[
u_{i,2}, \cdots, u_{i,K}, (i \in \{1, 2, 3\}) \quad y_{total,2}, \cdots, y_{total,K}, \quad z_{i,1}, \cdots, z_{i,K}, (i \in \{1, 2, \cdots, 6\}) \quad z_{as,1}, \cdots, z_{as,K}, \quad z_{risk,1}, \cdots, z_{risk,K}, \quad \delta_{i,1}, \cdots, \delta_{i,K}, (i \in \{1, 2\})
\]  

(37)

which minimize:

\[
J = \sum_{k=1}^{K} (\omega \cdot z_{risk,k} - z_{as,k})
\]  

(38)

subject to:

(25), (27), (28), (29), (33), (34), inequalities for \( z_{as,k} \), physical constraints, \( y_{as,k} \leq 0 \), \( \delta_{i,k} \in \{0, 1\} \).
The first term in the summation of the cost function (38) denotes the risk feeling index in Mode 1. The second term is a penalty to the assisting output. Note that the assisting output always takes a non-positive value, since we consider braking assist only. The effort of the assist can be controlled by the selection of the weight parameter $\omega$.

Generally speaking, the above MILP problem requires high computational cost. Actual computational time are evaluated and summarized in Table II. This evaluation was carried out using Intel Pentium 4, 3.2GHz and 1GB RAM. From this evaluation, we have set the horizon length $K$ as 5 so that the computation at every control cycle finishes within the sampling interval set as 200[msec].

<table>
<thead>
<tr>
<th>horizon</th>
<th>average [msec]</th>
<th>max [msec]</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>65.864</td>
<td>119.832</td>
</tr>
<tr>
<td>5</td>
<td>101.212</td>
<td>182.209</td>
</tr>
<tr>
<td>7</td>
<td>135.510</td>
<td>272.423</td>
</tr>
<tr>
<td>12</td>
<td>188.704</td>
<td>1190.005</td>
</tr>
<tr>
<td>15</td>
<td>282.251</td>
<td>4940.494</td>
</tr>
</tbody>
</table>

The experimental result is shown in Fig. 6. In Fig. 6, the bottom figure represents the profile of the assisting output. From this figure, we can see that the assisting system works only when the driving mode is Mode 1. According to the questionnaire after the experiment, the examinee did not feel any conflict with his original driving manner.

VI. CONCLUSION

In this paper, a personalized driver assisting system that makes use of a model of the driver’s behavior has been developed. The Probability-weighted ARX (PrARX) model has been employed to describe the driver’s decision making as well as continuous skill in a uniform manner. The parameters of the driver model have been identified using a simple gradient descent algorithm from actual driving data collected on a driving simulator. The obtained PrARX model is then transformed into a PWARX model. Finally, the optimization of braking assist is formulated as a MILP problem and computed online in the model predictive control loop.

Our current direction of research is to consider the driver’s ability to adapt to the change of driving situation and to the existence of assist itself. One way to take this into account is to introduce online identification of the driver model. Since the parameter estimation for PrARX models is done in a gradient-based manner, this model is quite suitable for the online identification scheme.

REFERENCES


