Driving Capability, a Unified Driver Model for ADAS

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Abstract. To allocate driving privilege in a reasonable way in shared control for intelligent vehicle, the study on driving capability, the unified driver model for ADAS in the longitudinal and lateral scenarios was proposed, which can improve the safety and comfort for intelligent vehicles as well. Driving capability is defined and analyzed and car-following stimulate in longitudinal scenario and moving double lane change stimulate in lateral scenario were designed. Data collection was conducted in Driver-In-the-Loop Intelligent Simulation Platform (DILISP). Driving capability identification model was established basing on Hammerstein process and Principal Component Analysis (PCA) was used to decouple and reduce the dimension for the key parameters in Hammerstein identification model. The classification is done basing on the particle clustering algorithm and the evaluation equation for driving capability was calculated by Multiple Linear Regression (MLR). Results show that the proposed evaluation method for driving capability in the longitudinal and lateral scenarios can achieve accurate and reliable evaluation results.

1. Introduction

The human-machine cooperative control of intelligent vehicle and intelligent transportation system needs to strengthened the understanding of driver behavior patterns. An accurate driver model and evaluation method of driver’s driving behavior patterns can allocate the driving privilege in a reasonable way and improve the safety and comfort for intelligent vehicles [1, 2].

The establishment of a reasonable driving right allocation mechanism is the key to achieve friendly human-machine collaborative driving interaction in the cooperative control system and a number of studies have been conducted. Soualmi B et al added a driving status monitor into the cooperative controller to allocate driving privilege to upper controller [3]. Guo et al realized the human-machine shared control basing on the evaluation of the natural driving confluence scenarios [4]. Dongkui Tan completed the driving privilege decision-making of human-machine collaborative control basing on the trajectory prediction method by establishing driving skill steering model [5]. It can be seen that exploring the driving status, driving style and driving skill in driver behavior patterns is of great significance for establishing a reasonable driving privilege allocation mechanism. However, the key components in the driving behavior pattern are coupled to varying degrees. Kang et al studied the coupling relationship of driving status, driving style and driving skill and their effects on traffic accidents [6]. By configuring different tyre-road friction coefficients in the driving simulator, Groot S.De et al analyzed the coupling relationship between driving skills and driving styles and the influencing factors [7]. Sun et al decoupled the driving style and driving skill basing on Hammerstein
process [8]. In summary, Driving status has strong randomness and complex variability and is weakly coupled with driving style and driving skill respectively, while driving style and driving skill are strongly coupled with each other.

The concept and evaluation model of driving capability in the longitudinal and lateral scenarios was proposed to solve the rationality problem of human-machine collaborative driving privilege allocation mechanism caused by the coupling and changeable characteristics of the elements in driver behavior patterns. Firstly, the significance of the proposed concept of driving ability is described and analyzed, and driving capability is defined. Secondly, car-following stimulate in longitudinal scenario and moving double lane change stimulate in lateral scenario are designed to collect driving capability data. Then the intrinsic attribute and characterization of driving ability are analyzed and the evaluation model is proposed. Thirdly, the driving capability identification model is established and the model parameters are decoupled and dimensionally reduced by Principal Component Analysis (PCA). The classification is basing on the particle clustering algorithm and the evaluation equation for driving capability was calculated by Multiple Linear Regression (MLR) finally.

2. Concept Description and Data Acquisition

2.1. Driving Capability Description

The coupling of key components of the driving behavior pattern and the human-vehicle-environment system based on it are shown in Figure 1. In the stimulate consisting of the traffic state, road condition and ego vehicle state, drivers generate specific driving intentions based on their driving styles, driving skills and driving status, and then maintain or change the state of the ego vehicle. There is a strong coupling between driving style and driving skill, and driving styles and skills are weakly coupled with driving status respectively.

![Figure 1. Coupling relationships between driving behavior components.](image)

Driving styles, driving skills and driving status are considered as independent factors in the current driving privilege allocation mechanism of the human-machine collaborative systems, as Eq. (1) shows.

\[ W_D = f(D_{sty}, D_{ski}, D_{stu}) \]  

(1)

Where \( D_{sty} \) is driving style, \( D_{ski} \) is driving skill and \( D_{stu} \) is driving status. Obviously, the forced decoupling of key components in driving behavior pattern will reduce the precision of driving privilege allocation.

2.2. Stimulate Scenarios and Stimulate Signals

In order to explore the driving capability mechanism and extract its intrinsic attributes, characterization and evaluation methods, the longitudinal and lateral stimulate scenarios and stimulate signals which can stimulate driving capability to the greatest extent are designed [9], as shown in figure 2. Five drivers aged between 25 and 40 with driving experience ranging from 2 to 10 years are selected as the tested drivers. As shown in Figure 2-a, the longitudinal scenario consists of a single-lane straight line, a traffic vehicle ahead and an ego vehicle. As shown in figure 2-b, inspired by the double-shift condition in BS ISO 3888-2:2011, a mobile double-shift scenario is designed as the lateral stimulate, including three traffic vehicles ahead and one ego vehicle. Traffic vehicles run in the velocity of 50km/h, and the driver in the ego vehicle overtakes in the velocity of 120km/h. The test...
time for a single longitudinal and lateral stimuli are [50, 60] s and [10, 15] s respectively. Driver needs to conduct cyclic tests repeatedly and continuously under the stimuli and the duration of each cyclic test is at least 6 hours. In the longitudinal and lateral stimuli, 10 groups of cyclic tests need to be completed respectively. If the driver has four consecutive traffic accidents in the virtual scene or subjectively expresses that he’s unable to continue driving, the test is completed.

**Figure 2.** Stimuli Configuration.

### 2.3. Driver-In-the-Loop Intelligent Simulation Platform

To collect driving capability data in longitudinal and lateral stimuli and ensure the safety, operability and repeatability of the test, a Driver-In-the-Loop Intelligent Simulation Platform (DILISP) is established based on dSPACE Simulator real-time simulation system and PanoSim intelligent driving simulation system. dSPACE DS1006 system is selected as the real-time simulation model processor and driving control signals inputs from the real accelerator pedal, brake pedal and SensoWheel torque steering wheel are received in real time. PanoSim software model runs in real time to obtain the ego vehicle state, the traffic vehicle state and their relative state.

### 3. Driving Capability Evaluation Model

#### 3.1. Logical Framework of Driving Capability Evaluation System

The framework of the driving capability evaluation system is shown in Figure 3. Driving capability can be expressed as a continuous value on the interval of [0, 1]. Value 0 corresponds to the worst driving capability and value 1 corresponds to the best driving capability. Driving capability data collected in longitudinal and lateral stimuli can input Hammerstein process based longitudinal and lateral identification models and model parameters of static and dynamic links can be obtained after model training. Basing on Principal Component Analysis (PCA), the independent parameter expression of decoupling and dimension reduction is obtained. After the particle swarm based classification, driving ability value and part of driving ability independent parameter calculation results are used to solve the driving ability evaluation equation, the others are used to verify the accuracy of driving ability evaluation equation.

**Figure 3.** Framework of evaluation method for driving capability.
3.2. Driving Capability Identification Model

Due to the time-varying, high-order nonlinear and dynamic characteristics of driving capability, Hammerstein identification process is selected as the Longitudinal and Lateral Driving Capability Identification Model (LonDCIM and LatDCIM), as shown in figure 4. Hammerstein identification process is composed of static nonlinear element and dynamic linear element in series. The input $S_t(k)$ of the driving capability identification model consists of ego vehicle state and the relative state between ego vehicle and traffic vehicle. DCIM outputs pedal signal or steering wheel angle signal according to model input and attribute. Therefore, LonDCIM and LatDCIM are both MISO systems.

\[
A(z^{-1}) \cdot O_p(k) = B(z^{-1}) \cdot z^{-d} \cdot N(k)
\]

\[
A(z^{-1}) = 1 + a_1 \cdot z^{-1} + \ldots + a_q \cdot z^{-q}
\]

\[
B(z^{-1}) = b_1 \cdot z^{-1} + \ldots + b_n \cdot z^{-n}
\]

Where $O_p(k)$ is the set of pedal signal $P_{ed}(k)$ consisting of braking and gas pedal and steering angle signal $A_{od}(k)$, $N(k)$ is the set $\{N_{lon}(k), N_{lat}(k)\}$ consisting of the output in static nonlinear element of DCIM, $q$ and $n$ are the orders in dynamic linear element and $d$ is the input delay order defined as the integer multiple of the sampling time.

3.3. Parameter Decoupling and Dimensionality Reduction

After a large number of driving capability data training, the model parameters in DCIM contained in the static nonlinear and the dynamic linear elements are the key data representing the intrinsic attributes of driving capability, so they are taken as the data samples for driving capability evaluation. To avoid the information overlap in data samples consisting of model parameters and ensure that the spatial dimension of data samples is reduced as much as possible on the premise of expressing the same model characteristics, the PCA method\cite{10} is adopted to decouple and reduce dimension the key parameters in the DCIM. Let $H=\{H_{lon}, H_{lat}\}$ represents model parameter dimension in DCIM and $E=\{E_{lon}, E_{lat}\}$ represents the number of single tests in a cycle test, the data set $X$ of $E$ observation variables corresponding to the parameters of the $H$-dimensional model parameters can be obtained as Eq. (8) and the steps of the PCA algorithm based on the parameter data set $X$ of the DCIM are shown in the figure 5.

\[
X = \begin{bmatrix}
x_{11} & x_{12} & \cdots & x_{1E} \\
x_{21} & x_{22} & \cdots & x_{2E} \\
\vdots & \vdots & \ddots & \vdots \\
x_{H1} & x_{H2} & \cdots & x_{HE}
\end{bmatrix} = [x_1, x_2, \ldots, x_E]
\]
The contribution rate of the principal component is defined as the percentage of the sum of the eigenvalues of the first \( m \) principal components and the sum of all the eigenvalues. The independent parameter dimension of the DCIM is determined by the cumulative contribution rate \( M_m \) of the principal component, as shown in Eq. (9).

$$M_m = \frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{E} \lambda_i}$$

(5)

Generally, the value \( m \) corresponding to \( M_m \geq 85\% \) is taken as the number of principal components, and the principal component matrix \( L \) with \( m \times E \) dimensions can be obtained eventually, as shown in Eq. (10).

$$L = \begin{bmatrix} l_{11} & l_{12} & \cdots & l_{1E} \\ l_{21} & l_{22} & \cdots & l_{2E} \\ \vdots & \vdots & \ddots & \vdots \\ l_{m1} & l_{m2} & \cdots & l_{mE} \end{bmatrix} = [l_1, l_2, \ldots, l_E]$$

(6)

3.4. Classification for Driving Capability

The classification results of typical driving capability are the basis of solving the driving capability evaluation equation. The model parameter samples of DCIM belong to the driving capability classification model set \( D_{cap} \).

$$D_{cap} = \{ \text{Stronger}, \text{strong}, \text{medium week}, \text{weaker} \}$$

(7)

The driving capability classification model mainly includes particle clustering process and the mapping process from the clustering results to the driving capability degrees. Compared with the genetic clustering and ant colony clustering, particles clustering has the advantage of fast convergence and memory of both location and speed. Clustering samples can be featured as \( L = \{ X_q, q=1, 2, \ldots, R \} \), where \( X_q \) is a vector with \( n \) dimensions. Clustering partition \( \omega \) can be feature as \( \omega = \{ \omega_1, \omega_2, \ldots, \omega_G \} \), and particle clustering process for driving capability is to seek out partition \( \omega \) in \( X_q \) that minimizes the total variation, which can be featured as Eq. (12).

$$J = \sum_{j=1}^{G} \sum_{X_q \in \omega_j} d(X_q, \bar{X}^{\omega_j})$$

(8)

Where \( \bar{X}^{\omega_j} \) is the \( j \)th clustering center points, \( G \) is the number of clustering centers, and \( d(X_q, \bar{X}^{\omega_j}) \) is the distance between \( X_q \) and \( \bar{X}^{\omega_j} \).

Since the clustering result doesn’t have physical meanings, it is necessary to establish the mapping relationship between the clustering result and each element in the set \( D_{cap} \). Let the tested drivers fill in the questionnaire for each single test, and elements in \( O_{CX} \) that has the largest intersection with the specific element in the set \( S_{CX} \) is the driving ability element of the same type. The single test contained in the intersection of elements is valid, and the rest is invalid, as shown in Eq. (13) and Eq.(14).
3.5. Driving capability evaluation equation

The training set consists of the $SO_{CX}$ and 3/5 data in $L$, and the validation set consists of the $SO_{CX}$ and 2/5 data in $\tilde{L}$. Then the driving capability evaluation equation can be featured as Eq. (15).

$$SO_{CX} = \bar{L} \cdot \beta$$

Where $\bar{L}$ is the subset of the driving capability independent parameter data set $L$ and $\beta$ is the regression coefficient. The expression of the variables is shown as Eq.(16).

$$\bar{L} = \begin{bmatrix} l_{11} & l_{12} & \cdots & l_{1e} \\ l_{21} & l_{22} & \cdots & l_{2e} \\ \vdots & \vdots & \ddots & \vdots \\ l_{m1} & l_{m2} & \cdots & l_{me} \end{bmatrix}; \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix}; SO_{CX} = \begin{bmatrix} SO_{CX,1} \\ SO_{CX,2} \\ \vdots \\ SO_{CX,e} \end{bmatrix}$$

The goodness of fit test (determination coefficient $R^2$), the overall linear significance test ($F$ test) and the variable significance test ($t$ test) are used as the statistical test indicators for the driving capability evaluation equation.

4. Result Analysis for Driving Capability

4.1. Result Analysis for DCIM

The inputs of longitudinal driving capability identification model are ego vehicle's jerkiness and acceleration, and the relative velocity and the longitudinal relative distance between the ego vehicle and the traffic vehicle. The output is the pedal position signal composed of the acceleration pedal position and the brake pedal position. The static nonlinear element selects the s-type function, the orders are $q=3$ and $n=3$ and $d=1$. Longitudinal identification and prediction results of NO.1 driver are shown in Figure 6. Figure 6-a shows identification results of the driver's longitudinal driving capability of NO.128 single test in the first longitudinal cycling test. Given that driving capability having the time-varying and gradual physical characteristics, drivers are numbered in the adjacent test to verify the validity of LonDCIM and the driving capability data of NO.129 single test in the first longitudinal cycle test are predicted, as shown in Figure 6-b. The calculation results of the identification and prediction fitting accuracy of the driver's LonDCIM are all above 85%, and the average identification and prediction fitting accuracy are 91.324% and 90.176% respectively.

![Pedal position](image1.png)

(a)

![Pedal position](image2.png)

(b)

Figure 6. Analysis of longitudinal driving capability identification model.
The inputs of lateral driving capability identification model are yaw rate and lateral velocity of the ego vehicle, longitudinal relative velocity relative displacement between the ego vehicle and the traffic vehicle ahead, the lateral relative displacement and longitudinal relative displacement between the ego vehicle and the lateral traffic vehicle. The output is the steering angle. The static nonlinear element selects the s-type function, the orders are \( q=3 \) and \( n=3 \) and \( d=1 \). Lateral identification and prediction results of NO.1 driver are shown in Figure 7. Figure 7-a shows identification results of the driver's lateral driving capability of NO.219 single test in the first lateral cycling test. Drivers are numbered in the adjacent test to verify the validity of LatDCIM and the driving capability data of NO.220 single test in the first lateral cycle test are predicted, as shown in Figure 7-b. The calculation results of the identification and prediction fitting accuracy of the driver's LatDCIM are all above 90%, and the average identification and prediction fitting accuracy are 94.468% and 93.606% respectively.

4.2. Results Analysis for Driving Capability Evaluation Equation

The driving capability classification results and effective value data set \( \tilde{L} \) of drivers in 6 cycle tests are taken as the training set and those in the rest 4 cycle tests are taken as the validation set. The training set for NO.1 driver in longitudinal driving capability evaluation equation are 1714 and 2683 groups respectively and the validation set for NO.1 driver in lateral equation are 1063 and 1526 groups.

Figure 8 shows the fitting results of MLR of driving capability of NO.1 driver in the first longitudinal and lateral cyclic test. The black point data is the single test number, classification results corresponding to the effective value data set \( \tilde{L} \) and the red point data is the fitting result based on MLR and the blue point data is the driving capability results of a single test corresponding to the invalid value calculated by the driving capability evaluation equation of NO.1 driver. It can be seen from the figure that the driver's longitudinal and lateral driving capability evaluation equation has a good fitting result.

\[
R^2 \text{ of the longitudinal and lateral driving capability evaluation equation for each tested driver are shown in table 1. } R^2 \text{ of each tested driver is close to 1, that is, the longitudinal and lateral driving}
\]

\[
\]
capability model has a high degree of goodness of fit. $F$-test values are shown in Table 2, it can be seen that $F^{>>}F_{ξ(e,e-m-1)}$ and there is a significant linear relationship between driving capability and the independent variables in driving capability evaluation equations.

| Table 1. Coefficients of determination of longitudinal and lateral driving capability equations. |
|---|---|---|---|
| Driver number | Coefficient of determination | Longitudinal | Lateral |
| 1 | 0.9842 | 0.9913 |
| 2 | 0.9616 | 0.9892 |
| 3 | 0.9837 | 0.9938 |
| 4 | 0.9913 | 0.9839 |
| 5 | 0.9744 | 0.9964 |

$t$-test results of the equations of NO.1 driver are shown in Table 3. When $ξ=0.1$, the longitudinal threshold $t_{ξ/2}(1714-14-1)=1.6458$ and lateral threshold $t_{ξ/2}(2683-21-1)=1.6454$. In the lateral and longitudinal driving ability evaluation equation, $t$-test values of each variable are all greater than the longitudinal critical value. Therefore, each variable has a significant impact on the driving capability of NO.1 driver. The same $t$-test results are obtained for other tested drivers, so all variables have significant influence on driving capability.

| Table 2. Results of F-criterion for longitudinal and lateral driving capability equations. |
|---|---|---|
| Driver number | Coefficient of determination | $Longitudinal F_{ξ(e,e-m-1)} / F$ | $Lateral F_{ξ(e,e-m-1)} / F$ |
| 1 | 1.70 / 127.49 | 1.56 / 276.83 |
| 2 | 1.65 / 89.63 | 1.56 / 255.49 |
| 3 | 1.67 / 109.58 | 1.55 / 213.60 |
| 4 | 1.70 / 132.45 | 1.53 / 287.14 |
| 5 | 1.70 / 94.21 | 1.55 / 283.26 |

| Table 3. Results of t-criterion for longitudinal and lateral driving capability equations. |
|---|---|---|
| Longitudinal $β_1,lon,...,β_{14},lon$ | Coefficient of determination | Lateral $β_1,lat,...,β_{21},lat$ |
| 2.5782, 1.7819, 2.0529, 2.3385, 3.0146 | 3.4896, 2.5730, 4.3816, 3.8924, 5.1110, 4.3948, 2.4269 |
| 1.8340, 1.7738, 2.3035, 2.1423, 1.9248 | 3.7300, 4.0397, 3.5621, 2.6349, 2.3412, 3.6548, 4.2671 |
| 2.0667, 1.6957, 2.7419, 1.9834 | 5.0614, 4.4440, 3.6729, 2.8491, 3.6782, 4.7740, 3.1678 |

5. Conclusion
To allocate driving privilege in a reasonable way in shared control for intelligent vehicle, the study on driving capability, the unified driver model for ADAS in the longitudinal and lateral scenarios is proposed, which can improve the safety and comfort for intelligent vehicles as well. Driving ability is the driver's ability to control the vehicle gradually with the change of scenario and a combination of personalized driving style, driving skill and driving status with time-varying nonlinear dynamic characteristics. Car-following stimulate in longitudinal scenario and moving double lane change stimulate in lateral scenario are designed. Data collection was conducted in Driver-In-the-Loop Intelligent Simulation Platform (DILISP). The Hammerstein identification process based longitudinal and lateral driving capability identification model is established with high identification and prediction fitting accuracy. Principal Component Analysis (PCA) was used to decouple and reduce the dimension for the key parameters in Hammerstein identification model. The classification is done basing on the particle clustering algorithm and the evaluation equation for driving capability was calculated by Multiple Linear Regression (MLR). In a large number of repeated tests, the driver's longitudinal and
lateral driving capability presents nonlinear time-varying and gradual physical characteristics. Driving capability shows volatility and randomness in several adjacent repeated tests. The goodness of fit test shows that the equation of longitudinal and lateral driving capability has good fitting results. The overall linear significance test of the equation ($F$ test) shows that the independent variables of the evaluation equation have a significant linear relationship with driving capability. The significance test of variables ($t$ test) shows that each variable of the evaluation equation has a significant impact on driving ability.

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