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Driving Capability-Based Transition Strategy for Cooperative Driving: From Manual to Automatic

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ABSTRACT In open traffic environments, humans still have to remain in the control loop of vehicle due to the insufficient of the existing technologies and their high costs. For the realization of cooperation between the human and the automatic driving system, the determination of the time when automatic driving is necessary is very important. To avoid unnecessary intervention when the driver has the control authority of vehicle, a new driving capability-based transition strategy was proposed, which comprehensively considers the driver's correction ability and the driving risk. The transition time from the human driver to the automatic driving system is determined by an unreliable domain (UD), whose boundary is modeled according to the driving data recorded by a driving simulator and statistically described by a log-normal distribution. Furthermore, an adaptive algorithm is designed to update the parameters of UD boundary online to make this strategy suitable for different drivers. This UD-based transition strategy is validated by several tests on the driving simulator. The bench test results show that the individual driving characteristic can be identified by the adaptive algorithm in time, the transition time determined by UD is more accurate, and sufficient time is reserved for the correction carried out by the automatic driving system.

INDEX TERMS Automatic driving, human-machine cooperation, driving capability, correction ability, driving risk.

I. INTRODUCTION

Traffic safety has always been an area of social concern, especially with the ever-increasing number of vehicles [1]. Driver error, the result of visual distraction or fatigue, is considered as a major contributor to traffic accidents. Hopes are being pinned on automatic driving technologies for their potential to enhance the sensitivity of driver to risk [2]–[4], help deal with dangerous traffic conditions [5]–[9], and even realize driving without human [8], [9]. However, due to the shortage of current automatic driving technologies and the high costs [10], driverless cars have not achieved the large-scale commercial applications. For the open and complicated traffic scenarios, a human driver still has to stay in the control loop of vehicle [11], [12]. So a cooperation realized by integration of both a human and a machine pilot has drawn much attention recently, because it allows them to be in the control loop of vehicle concurrently [13].

One way to combine the human and the machine control is to continuously allocate the control authority among them according to the evaluation of the driver's status. For both collision avoidance and lane-keeping conditions, Benloucif *et al.* designed a haptic shared driving control strategy [14]. But Winter *et al.* argues that the driving ability of driver diminishes with the application of such continuous shared systems and that it is critical for a cooperative driving system to ensure that the driving assistance is supplied only when the driver requires it indeed [15]. To avoid unnecessary assistance, evaluations of driver state, driving intention, and collision risk are all integrated into the cooperative driving system. The controls by the driver and the automated system are combined to generate the final input to the vehicle using the statistical optimization algorithm in [16] and fuzzy logic in [17]. Using a similar structure, Chen *et al.* designed a

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cooperative scheme for intersections considering both driver intention and risk [18]. The constraint of vehicle dynamic stability is further considered in [19]. Such cooperation strategies depend heavily on the reliable predictions of driver intention and driving trajectory. These are very challenging because of the dynamicity, uncertainty, and randomness of traffic [20].

Another method is to switch among the automatic driving system and the human according to the state of driver [21] or driving risk [22]. Tran *et al*. focused on the detection of fatigue, based on which a switching logic was designed to transmit the control authority from the driver to the machine pilot [23]. In that research, the fatigue is detected by combination of both steering operation and facial features of driver. A better detection accuracy of fatigue is achieved by combination of several types of signals with an intelligent classifier. Pohl *et al*. proposed a structure to realize cooperation for the lane-keeping task, whose control authority of steering is determined by the visual distraction of driver [24]. The head position and eye movement are combined together to detect the visual distraction. To enhance the adaptability and robustness of detection for the driver's distraction, Enache *et al*. fused the information of steering torque with the posture of driver body [25]. This cooperative system for steering control is applicable for different vehicle speeds and a variety of roads. Since both fatigue and distraction easily cause an accident, Benloucif *et al*. described these two driver states by a binary variable respectively, i.e., "critical fatigue or not" and "eye-off-ad or not". Then a comprehensive logic was designed to combine these two driver states together [26].

These switching strategies for cooperative driving based on driver's state have some disadvantages. First, the physiological measurement equipment is intrusive to drivers. It may disturb the normal driving process of driver, which is bad for traffic safety. Moreover, the usability and acceptability of such systems are also a problem. Furthermore, even if we can get the accurate information for "eye-off-road or not", a false judgement still may be generated by such short behavior of driver as adjusting the safety belt. Sentouh *et al*. was already aware of this when developing the switching logic and suggested a mandatory three-second delay to prevent such false interventions [27]. Another one is that driver state is not entirely equivalent to the driver's capability of keeping the vehicle in safe driving conditions. This implies that a distracted driver still can carry out the driving task safely, especially under the condition that the driving task is extremely simple. On the other hand, when the traffic condition is complicated enough, a wrong manipulation can also be performed by an attentive and skilled driver [28]. For instance, it is found from the studies of Liang *et al*. that the lateral driving ability of driver may be improved by cognitive distraction [29]. Moreover, each driver has its own driving manner [30] and so a cooperative driving system should be adaptable to various drivers.

In this article, to increase the accuracy and adaptability performance of switching logic from manual to automaticdriving, a new index is designed to measure the driver's correction ability, which is further integrated with the index of driving risk to construct a two-dimensional space for the evaluation of driving capability comprehensively. Then, a personalized unreliable domain (UD) is presented to design the switching logic from the manual driving to automatic driving. The boundary of the UD is modeled using the log-normal distribution according to the simulated driving data. Furthermore, an adaptive algorithm is designed to identify individual characteristics and update the UD parameters online.

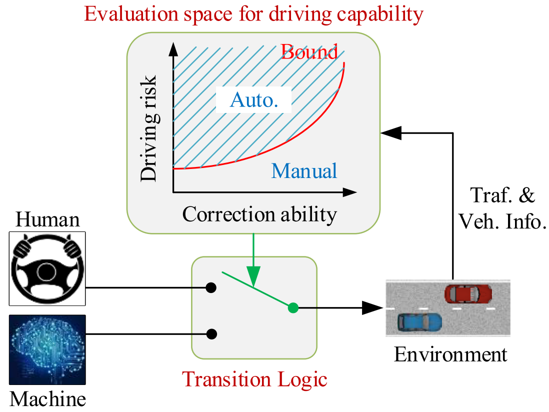

FIGURE 1. Scheme of driving capability-based transition strategy.

The rest of the paper is organized as follows: Section II introduces the fundamentals of the driving capability-based cooperative driving strategy; Section III establishes a personalized UD that can adapt to various driving styles and detect the switching time; in Section IV, the proposed strategy is validated and analyzed using a bench test; and Section V concludes the paper.

II. DRIVING CAPABILITY-BASED TRANSITION STRATEGY

With a cooperative switching structure, a new strategy for the transition from manual to automatic driving (shown in **FIGURE 1**) is proposed in consideration of the followings [27]–[29]: (1) All data required to evaluate the driving capability is in the information of vehicle and traffic, because these information includes all operations of driver; (2) It is critical for a cooperative driving system to guarantee that the assistance from an automatic driving is only supplied in a critical situation. Otherwise, the driver's ability tends to diminish; (3) Accordingly, if the driver can correct the vehicle to a safe condition even the driving risk increases, the control authority of vehicle still should be given to driver.

Since the measurement of driver's state requires additional wearable equipments or is sensitive to the environment [23]–[26], only the signals obtained by the onboard sensors are used to determine the switching time. To avoid unnecessary interventions when the driver has the ability to correct the vehicle state, a new index called "correction ability" is designed and integrated with the index of driving risk to determine when to assist the driver. Here, the driving capability is used to comprehensively measure the driving risk and the correction ability of driver. Though only two types of indexes are considered, other human factors, such as fatigue and distraction, can be measured by them indirectly. Because if the driver state regresses to an unacceptable condition, the driving risk will increase and his/her actions also may deviate from the normal ones.

With the proposed measurement indexes, a two-dimensional evaluation space including both correction ability of driver and driving risk is set up to comprehensively evaluate the driving status. The former is to measure the driver's ability to keep the vehicle in safe driving conditions. The latter characterizes the risk of collision with other road objects. Automatic driving is preferred under the condition that the correction ability of driver is not enough and the collision risk is comparatively high. Considering these fundamentals, the following switch-based cooperative logic is designed:

$$\begin{cases} \boldsymbol{x}_d \in \boldsymbol{\Omega}, & \text{Automaticdriving} \\ \text{Otherwise}, & \text{Manualdriving}, \end{cases} \quad \boldsymbol{x}_d = \begin{bmatrix} \varepsilon_r \\ \varepsilon_c \end{bmatrix} \tag{1}$$

Here, $\boldsymbol{x}_d \in \mathbb{R}^2$ is the driving status, ε_c, ε_r are the correction ability and driving risk respectively, and $\boldsymbol{\Omega}$ is UD (Shadow area in **FIGURE 1**) which is a set composed of all unreliable driving states. Being different from the shared control strategy studied in [31] and [32], this cooperation strategy switches the control authority of vehicle among the human driver and the automatic driving system. If the driver status is judged to be out of UD, only the human driver can control the vehicle. On the contrary, the human driver will be replaced by the automatic driving system totally. How to construct $\boldsymbol{\Omega}$ is investigated in Section III Here the transition logic for lateral and longitudinal cooperation are conducted separately, but they have the same formula as (1). This implies that the steering is controlled by the automatic driving system, while the powertrain/braking may still be manipulated manually. Compared with existing switching strategies, this provides assistance only when the condition is dangerous and the driver cannot overcome the risk. Moreover, with the adaptive algorithm for updating the UD parameters introduced in Section III. C., this logic can adapt to various driving styles.

A. MEASUREMENT INDEX OF DRIVING CAPABILITY

For the development of advanced driver assistance systems, such as forward collision warning system and lane departure warning system, several types of indexes have been proposed to determine the trigger time of warning. In those researches, the time to collision (TTC) [30] and the time to line crossing (TLC) [33] are widely used for the evaluation of longitudinal and lateral driving risk, respectively. Therefore, in this article, TTCi (TTC is replaced by TTCi to avoid dividing by zero) and TLC are used to measure the driving risk:

$$\begin{aligned} \text{Lateral} : \text{TLC} &= (d_L - L/2) / (v \sin \alpha) \\ \text{Longitudinal} : \text{TTCi} &= v_r / d_r \end{aligned} \tag{2}$$

Here, d_L is the distance from vehicle centroid to lane boundary, L is the width of vehicle body, v is the vehicle speed, α is the angle between driving direction and road direction, v_r and d_r are the relative speed and distance respectively.

Though there exist many indirect or direct approaches to detect and evaluate the driver state [21], correction ability is difficult to characterize since it measures the driver's ability to manage the vehicle in risky traffic scenarios. There are few studies about the measurement of correction ability. In this article, to propose the evaluation index of driver's correction ability, the following assumptions are made:

(1) A driver has particular driving commands when he/she drives in a specific traffic scenario.

(2) As well, the actual driving command of a driver will be similar with the desired one when he/she has enough manipulation ability.

Therefore, the deviation of the actual driving command from the desired one is chosen to evaluate the correction ability:

$$\begin{aligned} \text{Lateral} : \epsilon_{cla} &= |\delta_a - \delta_m| \\ \text{Longitudinal} : \epsilon_{clo} &= |a_a - a_m| \end{aligned} \tag{3}$$

Here, ϵ_{clo} and ϵ_{cla} are the longitudinal and lateral correction abilities, δ_a and a_a are the actual steering angle and longitudinal acceleration, δ_m and a_m are the desired steering angle and longitudinal acceleration, respectively.

The desired driving commands are calculated by the driver's model. Referring to the analysis conducted by Wang *et al*. about the factors affecting the lateral driving behavior [33], the same signals including relative yaw angle, vehicle speed, road curvature and lateral distance are selected as the inputs of the lateral driving model. Referring to [34], which used only range and relative velocity as the inputs to the longitudinal model, road curvature and speed of ego-vehicle are further added to cover more complicated conditions. Since the behavior of driver is random, nonlinear and individual in real traffic conditions, the Artificial Neural Network for Nonlinear Autoregressive Exogenous Process (ANN-NARX) is selected to model the driver behavior because of its advantages of both ANN and NARX [35]. Moreover, it is known from the previous studies that a driver's response time is around 0.45–1 s [37], so an input delay of 0.7 s is added to ANN-NARX. This model calculates the desired driver inputs and will be trained by Levenberg–Marquardt [36] using the simulated driving data in Section III. B.

III. PERSONALIZED UNRELIABLE DOMAIN DESIGN

With the measurement indexes for driving capability presented in Section II. A., the following UD for cooperation is proposed:

$$\begin{aligned} \boldsymbol{\Omega}_{lo} &= \left\{ \begin{array}{l} \text{TTCi} > \underline{\text{TTCi}} \text{ and} \\ \epsilon_{clo} = |a_a - a_m| > \sigma_{clo} \end{array} \right\} \\ \boldsymbol{\Omega}_{la} &= \left\{ \text{TLC} < \overline{\text{TLC}} \text{ and } \epsilon_{cla} = |\delta_a - \delta_m| > \sigma_{cla} \right\} \end{aligned} \tag{4}$$

Here, $\boldsymbol{\Omega}_{la}$ and $\boldsymbol{\Omega}_{lo}$ are the UDs for lateral and longitudinal cooperation, σ_{cla} and σ_{clo} are the thresholds of correction ability for lateral and longitudinal cooperation,

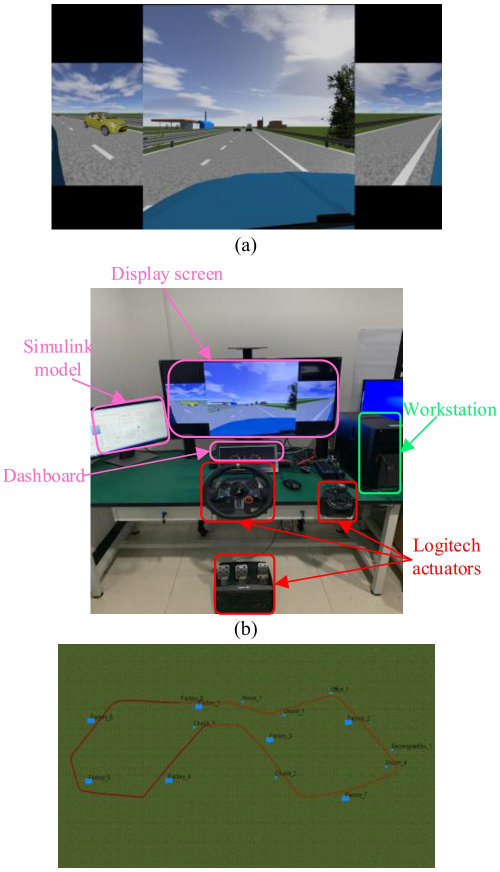

FIGURE 2. **Driver simulator for data collection and validation. (a) Displayed traffic scenario. (b) System structure. (c) Driving trajectory.**

$\overline{TLC}$ and $\underline{TTCi}$ are the limits of driving risk for lateral and longitudinal cooperation, respectively. The actual driving commands of driver, a_a and δ_a, can be obtained from the onboard network. The desired control values, a_m and δ_m, are calculated by the ANN-NARX driver model trained in Section III. C. It is known from the previous studies that different drivers have obvious individual driving characteristics. So this UD-based transition strategy should not only find the necessary assistance more accurately but also be applicable to different users.

A. DRIVER SIMULATOR AND TEST SCENARIO

To analyze the influence of driving style on UD and train the driver model, a driver in loop test platform was set up and used to acquire the driving data for safety, efficiency and cost. The driver simulator is set up as **FIGURE 2** (a), where the commercial software for the simulation evaluation of automatic driving systems, Prescan, is adopted to simulate the traffic scenario and the vehicle dynamical behavior is provided by a real-time simulator from dSPACE including the hardware system, MicroLab, and the vehicle dynamical model, ASM [39].

The road length is about 70 km and there exist several curves with different curvatures as shown in **FIGURE 2** (c). When conducting the tests, such vehicles as buses, passenger cars and trucks are deployed and run randomly. The surrounding vehicles are limited to the velocities under 160 km/h, and accelerate/decelerate in the range of $[-0.8g, 0.5g]$, where g is the gravitational acceleration.

Here, the driver simulator is used to acquire the driving data and validate the proposed cooperation strategy in consideration of the following factors:

(1) The driving capability will be degraded by distraction and accordingly a collision easily happens. This leads to critical problem of experiment safety if the real vehicle test is adopted;

(2) The driver is disturbed by many unknown and uncontrollable factors in real traffic environments. This causes difficulty on the analysis of driving capability under different conditions.

B. TRAINING OF DRIVER MODEL

It is known from (4) that a driver model should be established firstly to calculate the index for correction ability. Ten drivers, including 3 females and 7 males, have participated in the tests. All of them have driven no less than 1,500 miles and held the licenses no less than 2 years. The driver controls the vehicle naturally, and no interference is permitted.

The statistical results of the simulated driving data are compare with the naturalistic driving one in **FIGURE 3**. The natural driving data is collected in Chongqing, China [6]. The trajectory is about 30 km including highways, urban expressways and roundabouts, and a total of 20 sections of driving data are recorded. As shown in **FIGURE 3**, the overall distributions of vehicle states are similar. The naturalistic driving scenario is relatively more steady because the trajectory is mainly composed of highways and expressways. On the contrary, the behavior of road users in the simulated scenarios is generated randomly, and so the traffic scenario is more dynamical.

To characterize the driving behavior, an ANN-NARX model with 1 hidden layer and 10 neurons in each hidden layer is used and the simulated driving data is divided into train set and test set with the ratio of 7:3. Table 1 shows the mean square error (MSE) of the trained ANN-NARX model. It is concluded from the result that the trained model can predict the driving behavior accurately for both longitudinal and lateral motions.

C. ADAPTIVE ALGORITHM FOR INDIVIDUAL DRIVING STYLE

To avoid triggering assistance incorrectly, the designed UD should exclude all normal and safe driving conditions. Therefore, it is the best to construct the UD using the data under both abnormal and normal driving conditions. It should also be considered that the driver's behavior is less certain and less consistent especially under critical and abnormal scenarios. This is bad for the convergence and stability of training process, so the data recorded under normal driving conditions by the driving simulator is used to determine the boundary of UD (See section III. A.). The statistical

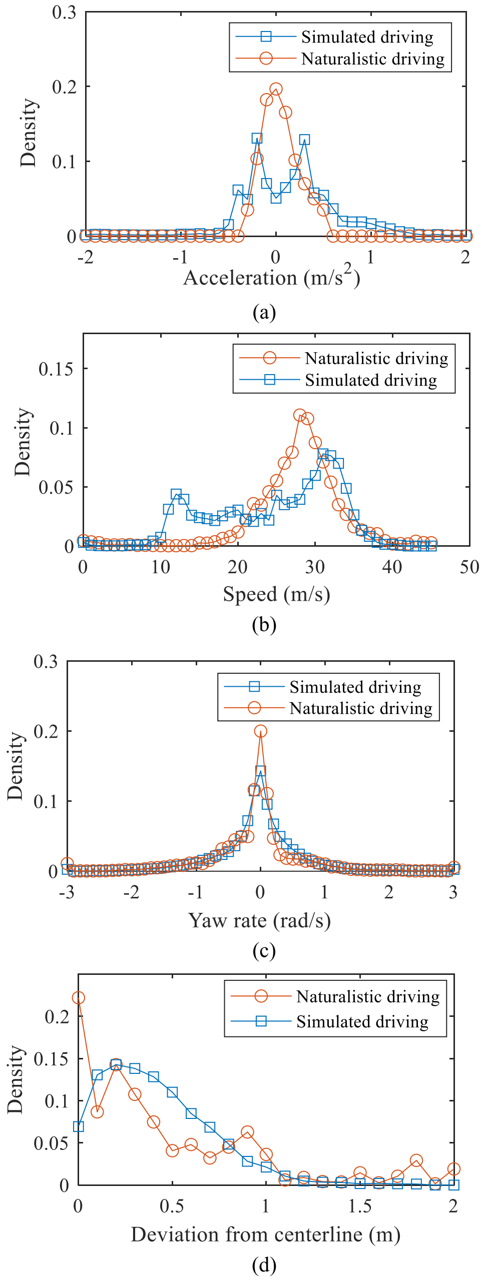

FIGURE 3. **Comparative results of simulated and naturalistic driving data. (a) Vehicle acceleration. (b) Vehicle speed. (c) Yaw rate of vehicle. (d) Deviation of vehicle centroid from centerline.**

TABLE 1. **Accuracy of driver model.**

	Lateral [deg^2]	Longitudinal [m^2/s^4]
Training MSE	0.189	0.0129
Test MSE	0.186	0.0130
Average MSE	0.188	0.0129

results related to correction ability and driving risk are shown in **FIGURE 4**.

It is found from the statistical results in **FIGURE 4** that all driving capability indices accord with the log-normal distribution. This makes it possible to identify the real time boundary of UD for the adaptability of the transition strategy to different users. The parameters of a log-normal distribution can be obtained from the sample values by

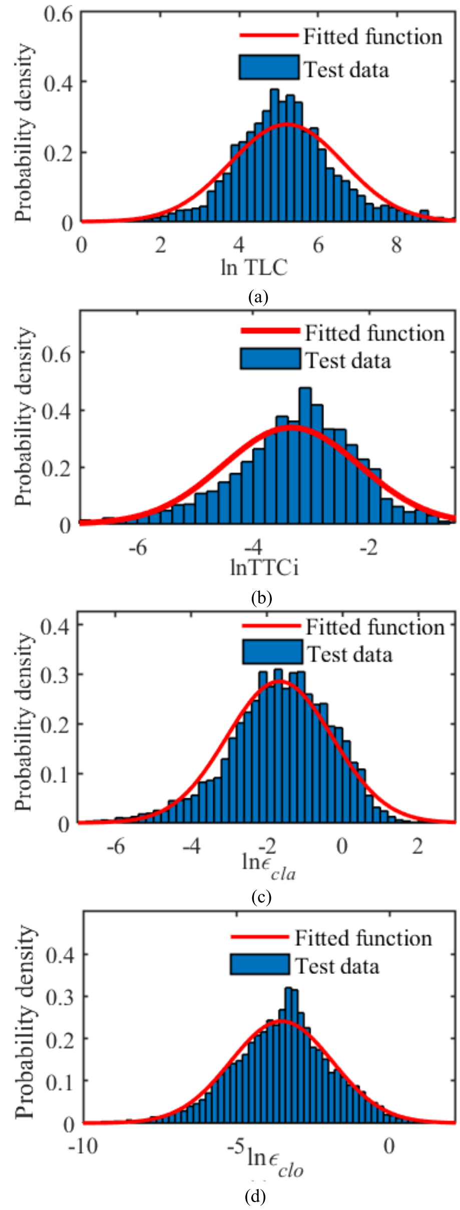

FIGURE 4. **Statistical results of driving capability. (a) Lateral driving risk. (b) Longitudinal driving risk. (c) Lateral correction ability. (d) Longitudinal correction ability.**

$$\mu = \frac{1}{N}\sum_{i=0}^{N}\ln\varepsilon_i, \quad \sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(\ln\varepsilon_i - \mu)^2 \tag{5}$$

where μ and σ are the mean and variance, ε_i is the sample value and N is the number of samples. Then the cumulative density function (CDF) is

$$F(\ln\varepsilon) = \frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{\ln\varepsilon} e^{-\frac{(\ln\varepsilon-\mu)^2}{2\sigma^2}} / \ln\varepsilon \, d_{\ln\varepsilon} \tag{6}$$

where $F(\ln\varepsilon)$ is the CDF.

In **FIGURE 4**, the fitted distribution functions for different measurement indexes are represented by the red ones. With these distribution functions, the UD's boundary can be obtained by a confidence value and the inverse CDF as

$$\varepsilon = e^{F^{-1}(\bar{p})} \tag{7}$$

where $\bar{p}$ is the predefined confidence value. For a new sample ε_i, the probability that ε_i is smaller than ε is $\bar{p}$. For different indexes of driving capability, the calculation process of UD's boundary is the same as (5)∼(7), but the used sample value is different. Here, the confidence value of the longitudinal driving risk, the longitudinal and the lateral correction ability is set to $\bar{p} = 0.95$. But the confidence value is set to $\bar{p} = 0.05$ for the lateral driving risk, since its UD is smaller than the threshold (See the definition of $\mathbf{\Omega}_{la}$ in (4)).

It is known that the driving styles of different drivers may be quite different, so this UD-based cooperative strategy is required to adjust its parameters adaptively according to the actual driving data in time. The following adaptive algorithm is designed to calculate the CDF parameters of UD boundary recursively with new values at the current sample time k [38]:

$$\mu_k = \frac{\ln\varepsilon_{k-1} + N_{k-1}\mu_{k-1}}{1 + N_{k-1}},$$
$$\sigma_k^2 = \sigma_{k-1}^2 + \frac{N_{k-1}}{1 + N_{k-1}}(\ln\varepsilon_{k-1} - \mu_{k-1})^2 \tag{8}$$

With (8), only the data at the former and current sampling periods is needed and it is not necessary to store all historical data.

D. ADAPTABILITY TO DIFFERENT DRIVERS

The key consideration of this study is that even the driver is distracted, he/she may still have the ability to manage the vehicle in a risk-free state especially when the traffic scenario and the driving task are very simple. It is necessary to deal with the individual difference of this ability when designing the cooperative driving system. The main of the designed cooperative strategy is the UD, and the interactive process for updating UD parameters during the bench test is shown in **FIGURE 5** (Only two drivers are selected as an example).

From the results shown in **FIGURE 5**, the following can be seen:

(a) Although the predefined boundary of UD doesn't accord with the corresponding driver, the estimated parameters of UD boundary converges after 900 s;

(b) Since different drivers always have different driving characteristics, the boundary parameters of UD for Drivers 1 and 2 are not the same.

It can be concluded from those results that the designed statistical model of the UD boundary with the online updating algorithm described by (6)–(8) can not only estimate the boundary parameters of UD, but also identify the individuality of different driving behaviors.

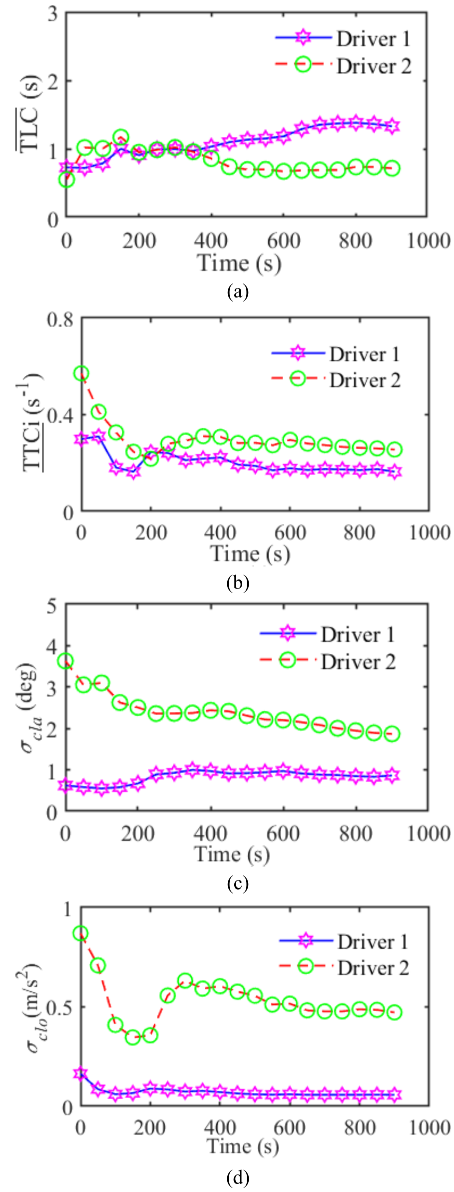

FIGURE 5. Updating of UD parameters. (a) Lateral driving risk. (b) Longitudinal driving risk. (c) Lateral correction ability. (d) Longitudinal correction ability.

IV. APPLICATION VALIDATION

This section validates the proposed switch-based strategy for the transition from manual to automatic driving using the driving simulator with the same traffic scenario (See **FIGURE 2**). It is different from fatigue that distraction is difficult to be activated consciously and measured quantitatively. Since multiple resources of the driver including visual, manual and cognitive are needed cooperatively to carry out a visual–manual (VM) task, this type of distraction is adopted to simulate distraction during the bench tests [40]. The designed VM task requires the driver to perform a calculation on a mobile phone, which is placed at his/her side. The computational complexity reflects the degree of degradation of driving capability. Another 10 drivers participated in the bench validation. There are 3 females and 7 males ranging

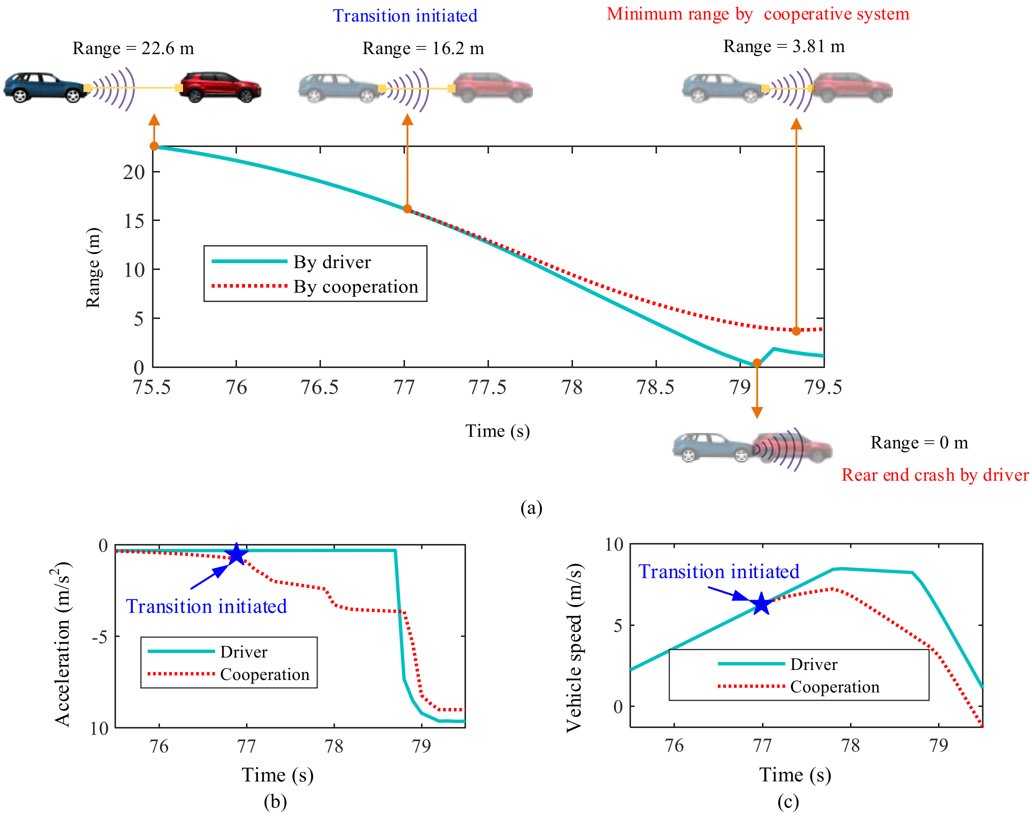

FIGURE 6. **Longitudinal cooperative driving. (a) Longitudinal cooperation scenario. (b) Acceleration. (c) Velocity.**

in age from 23 to 48. All of them have driven no less than 1,500 miles and held the licenses no less than 2 years.

Before the test, to ensure the convergence of the estimation of the boundary parameters and be familiar with the driving simulator, the participant drives naturally for about 20 min without the VM task. When carrying out the tests, the participant is asked to conduct 45 VM tasks by a voice signal randomly to ensure that he/she is unaware of the distraction task in future. Given that if the duration of distraction is too long, an accident easily happens [41], the maximum duration of distraction task is limited to be smaller than 15 s.

A. ACCURACY OF UD-BASED TRANSITION STRATEGY

Since a false negative event is that there is no driving risk in real and the driving status is also outside of UD. This is the normal driving process of human driver, which constitutes a very high proportion of the experimental data by comparison with other types of events. To ensure the significant of statistical index, the false negative events are not considered and the following ones are used to analyze the performance of UD-based transition strategy:

- TP (True positive): A TP event is that the driving status is in the UD, and at the same an actual high-risk event occurs, such as rear-end collision and lane departure.
- FP (False positive): An FP is an event that the driving status is classified to be in UD wrongly, but there doesn't exist any risk.
- TN (True negative): A TN event is that a real driving risk occurs, but the driving status is outside of UD.

This part focuses on the accuracy of the UD, which is evaluated by the following statistical index:

$$\lambda_a = N_{TP} / \left(N_{TP} + N_{FP} + N_{TN}\right) \tag{9}$$

Here, λ_a is the accuracy, N_{FP}, N_{TP} and N_{TN} are the number of *FP*, *TP* and *TN*, respectively. To test the accuracy of UD-based detection for driving capability objectively, even when the driving status is in UD, the assistance from the automatic driving system will not be carried out. The high-risk events, *i.e.*, rear-end crash and lane departure are chosen as the objective index.

During all tests, there are totally 275 real lane departures and 251 are successfully identified by UD and the detection accuracy is 91.3%. For the longitudinal driving, there are 139 rear-end collisions and UD detects 123 with an accuracy of 88.4%. By integration of the correction ability with the driving risk, the unnecessary assistance is successfully prevented and so there is no FP event.

To further analyze the relationship between the driver state and the high-risk events, the lateral driving events are categorized as shown in IV-B. Here, if the driver is asked to perform a VM task, the driver is considered as distracted until the task is completed. The result shows that there exist 105 distractions during which the driver still can control the vehicle within the lane. This implies that the driver may have sufficient ability to control the vehicle even he/she is distracted. Accordingly, the switching accuracy can benefit from the introduction of the index of correction ability of the driver.

TABLE 2. Lane departure and distraction events.

Type	Number
Departure with distraction	367
Departure without distraction	134
Distraction without departure	105

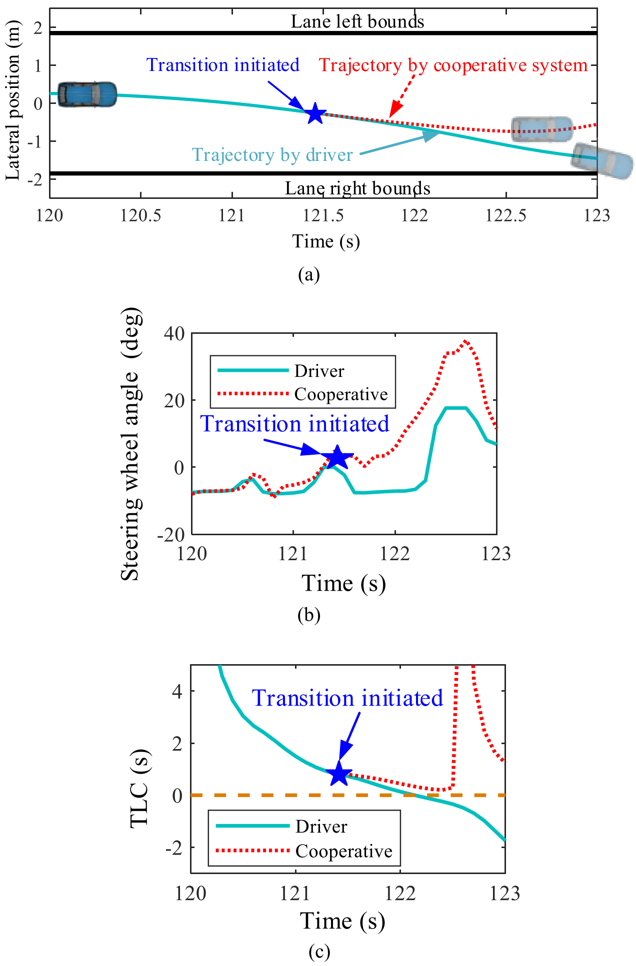

FIGURE 7. Lateral cooperation. (a) Lateral cooperation scenario. (b) Steering angle. (c) TLC.

B. PERFORMANCE OF COOPERATION SYSTEM

It can be concluded from the test results in section IV. A. that the new index for the evaluation of driving capability can accurately identify the switching time. Here, the driving process of the UD-based cooperation is further tested to validate that whether enough correction time is reserved to drive the vehicle to a risk-free state by the automatic driving system. Since the transition logic from manual to automatic driving is focused by this study, the trained ANN-NARX model in section III. B. acts as the automatic driving control algorithm after transition to realize the whole cooperation system. Some typical longitudinal and lateral cooperative driving scenarios are selected as examples and shown in **FIGURE 6** and **FIGURE 7**, respectively.

FIGURE 6 shows a longitudinal cooperative driving scenario. In this scenario, the driver is distracted at about 75.5 s by a VM task, which lasts about 3 s. After distraction, the driver loses the ability to evaluate rear-end collision risk and the distance decreases gradually. At about 78.7 s, the driver completes the task and presses the brake pedal immediately and firmly to avoid collision. Although the deceleration reaches maximum road adhesion, a collision still occurs at about 79.1 s because the relative distance is too short to stop the vehicle safely. If assistance is triggered by the driver state, the automatic driving algorithm will be activated at about 75.5 s. From **FIGURE 6** (b), it can be seen that in the early stage of distraction, the predicted acceleration is close to the driver's command, which means that the driver still has the ability to remove the driving risk and assistance is not necessary. The UD activates the automatic control algorithm at about 76.9 s, after which the acceleration decreases noticeably and reaches maximum road adhesion at about 79.2 s. As shown in **FIGURE 6** (a), the clearance between the two vehicles is 3.81 m after stopping, which is enough to ensure safety. From the results in **FIGURE 6** (b) and (c), the driving authority is changed smoothly from manual to automatic.

FIGURE 7 shows a lane departure scenario. The vehicle departs gradually from its lane at about 123 s because the driver is distracted at 120 s. The distraction task lasts more than 2 s, and the driver tries to control the vehicle to the center of the lane after 122.2 s. Because it is too dangerous to turn the steering wheel sharply, the vehicle departs from the lane anyway. At the earlier stage of distraction, as shown in **FIGURE 7** (c) the TLC is larger and the risk of lane departure is very low. With an increase in distraction time, the TLC decreases to less than 1.5 s at about 121 s, which is always considered dangerous [33]. But the automatic control algorithm is not activated by the UD until 121.5 s because the predicted steering angle is still close to the driver command and the driver has the ability to correct the vehicle state, as show in **FIGURE 7** (b). Then, the vehicle gradually returns to the center of the lane and the TLC is greater than zero during the complete lateral cooperative driving process. This implies that the vehicle does not enter the adjacent lane (See **FIGURE 7** (c)).

V. CONCLUSION AND FUTURE WORK

In this article, a new evaluation index of correction ability is designed and further integrated with the driving risk to formulate a two-dimensional space for the evaluation of driving capability. Based on this, a statistical model was set up for a UD boundary to realize adaptation to various driving styles. From bench test results and analysis, the following conclusions are achieved:

(1) The proposed UD could accurately detect the time when assistance is need by integration of the driver's correction ability with the driving risk.

(2) The statistical model of the UD boundary can identify an individual driving style. The updating algorithm for the parameters of the UD boundary was convergent and could

complete the identification process within an acceptable time.

(3) The UD-based strategy for transitioning from manual to automatic driving was effective. Both longitudinal and lateral risk events could be identified and avoided successfully, and the transition process from manual to automatic was sufficiently smooth.

Some open questions are worthy to be further investigated as follows:

(1) This study is based on the data acquired from the simulated driving system, which is not totally the same as the real one. In the practical traffic, the driving behavior may be more complicated.

(2) The decrease of driving capability is simulated by the VM tasks in this study, which is just one of the factors reducing the driving capability. It is better to evaluate the designed cooperative driving strategy considering more factors such as fatigue, drugs, alcohol and so on.

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