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ADAS Acceptability Improvement Based on Self-Learning of Individual Driving Characteristics: A Case Study of Lane Change Warning System

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ABSTRACT Low user acceptance is one of the fundamental problems for popularizing advanced driver assistance systems (ADAS). Systems that are developed for the majority of drivers have to possess stationary characteristics and be conservative for safety reasons. However, the drivers with disparate driving styles possess different risk cognition of lane change behavior; therefore, such systems with stationary characteristics may cause frequent interference to aggressive drivers or may be perceived as a radical system by conservative drivers. An ADAS that adapts to the characteristics of individual drivers during lane change maneuvers will be more effective and more acceptable to drivers. In this study, we developed an adaptive algorithm that learns the characteristics of individual drivers during lane changes and determines the optimal threshold online to adapt to different drivers. Signal detection theory (SDT) was employed and the results of the accuracy, false negative rate, and false positive rate were used to capture the drivers' lane change behavior characteristics. A learning stage and a threshold fluctuation stage were designed in the adaptive algorithm to determine the optimal warning threshold and amended the optimal warning threshold based on changes in the drivers' behaviors. We evaluated the proposed algorithm by conducting the actual vehicle tests with a total of three participants. The offline statistical analysis results of the participants' lane change characteristics were compared with the online results of the warning threshold adjustments from the adaptive algorithm; the comparison results indicated that the adaptive algorithm could effectively capture the drivers' lane change characteristics and determine an appropriate warning threshold. The findings provide an improvement in the performance of the lane change warning (LCW) system and enhance people's acceptance of intelligent systems.

INDEX TERMS Self-learning, lane change characteristics, lane change warning system, signal detection theory.

I. INTRODUCTION

Lane change warning (LCW) systems have been applied increasingly in intelligent vehicles to enhance the safety of lane changes and reduce driver workload [1]–[3]. An LCW system provides a warning of impending conflict based on an analysis of the kinematic states between a subject vehicle and a target vehicle [4]. The benefits of LCW systems in improving the safety of lane changes have been adequately demonstrated [5], [6]. However, an ordinary warning threshold used in an LCW system developed for the average driver does not adapt to different driving styles. In practical driving conditions, there are distinct discrepancies in driving styles and safety requirements among individual drivers [7]. In addition, even the same driver may exhibit different driving characteristics under different driving conditions [8]. These

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individual differences and state fluctuations have resulted in considerable difficulties in LCW systems design and also make the acceptance of LCW systems an enormous challenge. Therefore, the prompt and accurate adaptation of an LCW system to different driving behaviors is a key objective in LCW algorithms exploiting.

At present, it is difficult for an LCW system to automatically capture the driving characteristics of a particular driver on account of the static LCW thresholds used in the LCW system. Drivers with different driving characteristics possess different cognition of the risk associated with lane change behavior [9]–[11]. For example, prudent drivers are more inclined toward cautious operations and may even deem reasonable lane change behavior as dangerous driving. Therefore, an LCW system with a relatively small time-to-collision (TTC) warning threshold might be regarded as unsafe by prudent drivers. Inversely, the conservative TTC warning threshold for prudent drivers may be regarded as overcautious alarm by aggressive drivers and the annoyance of premature warning may reduce driver trust in the LCW system. Hence, multifarious methodologies have been exploited in an effort to improve the acceptance of LCW systems according to different driving behavior characteristics. Zhu et al. [12] analyzed the personalized lane change time and personalized safety margin of lane change behavior deduced from driving simulator experiments to classify driving styles into three categories: cautious, normal, and aggressive. A personalized LCW strategy was proposed based on different driving styles. Wakasugi [13] proposed an appropriate warning time model for an LCW system based on different steering behavior obtained from the results of on-road experiments. In addition, an LCW threshold according to different traffic environments may also reduce the limitations of LCW systems. In the ISO 17387:2008 standard [14], different TTC warning thresholds are determined based on the relative approach velocity between the subject vehicle and a target vehicle in the adjacent lane. Although LCW thresholds based on different driving styles and different traffic environments can improve the acceptance of an LCW system, static LCW thresholds still do not fit the diversity of driving styles and the different driving conditions.

An LCW system can be effective if the driving characteristics of individual drivers are captured and the LCW thresholds are adaptable to different drivers. Over the years, researchers have pursued various approaches to improve the self-adaptive ability of LCW algorithms. There are two common methods to improve the adaptability of LCW models, i.e., machine learning models and mathematical optimization models. Based on the analysis of naturalistic driving data, the objective of machine learning models is to structure the relationship between different driving styles and personalized LCW strategies [15], [16]. Mathematical optimization models are designed to identify the personalized parameters of the established LCW models [17], [18]. At present, commonly used machine learning modeling techniques include the artificial neural network (ANN) model, hidden Markov model (HMM), fuzzy model, support vector machine (SVM), Bayesian network, and Gaussian mixture model (GMM) [19], [20]. These models are very effective in terms of model adaptability to different drivers and accuracy improvement due to sufficient training data based on naturalistic driving. However, the established models are viewed as a black box system and the parameters of these models often lack physical meaning [21]–[23]. Mathematical optimization models comprise least mean squares (LMS), least squares (LS), recursive least squares (RLS), and maximum signal-to-noise ratio (MSNR) approaches. Numerous empirical studies have been conducted to investigate adaptive LCW strategies. Toshiya et al. [24] developed a framework of a customized driving support system for individuals with different driving characteristics based on a fuzzy logic and a neural network. The driving simulator experiments indicated that the proposed model captured the personal driving characteristics and adapted to different drivers. Wang et al. [25] established a dynamic learning model of driving characteristics by combining the GMM and HMM. A vehicle trajectory prediction model was employed to develop a warning strategy for a lane departure warning system and the experimental results indicated that the proposed method can significantly reduce the false-warning rate. A personalized driver lane change model with a two-layer sub-models for driver assistance systems was proposed by Vadim and Ioannou [26]. A kinematic lane change model was described by the lower layer and the kinematic model parameters for different drivers were self-adjusted in the higher layer. Li et al. [27] proposed a lane change intent estimation model by combining the GMM and Bayesian network for drivers with different driving styles. Zhang et al. [28] established a self-learning model for different driver characteristics. The LS method was employed for the online identification of the driver's model parameters and a neural network was used to automatically match the parameters to the different drivers.

LCW models are an essential component of the design of adaptive algorithms and various approaches have been pursued to establish the most appropriate warning indicators and warning criteria that conform to a driver's perception of lane change safety. Gipps [29] proposed a lane change decision model for the microscopic traffic simulation. In this model, if the requisite deceleration for lane change was smaller than -4 m/s^2, the lane change operation was regarded as unsafe behavior. Hossein et al. [30] employed the minimum longitudinal safe distance between the subject vehicle and rear vehicle in the target lane during lane changes to determine the safety boundary and the minimum safe spacing (MSS) model was established based on the analysis of naturalistic driving data. Wang et al. [31] combined the minimum safe distance and the anticipated deceleration of the rear vehicle to develop an ameliorative LCW indicator. In recent years, many studies have focused on confirming the most suitable TTC value as an LCW indicator. A warning algorithm combined with the TTC threshold and the distance between the subject vehicle and rear vehicle in the target lane was proposed by the Bosch company [32]. In detail, the TTC warning threshold was 3.5 s if the longitudinal distance between the rear bumper of the subject vehicle and rear vehicle in the target lane was in the range of 3 m to 25 m; when the distance ranged from 25 m to 45 m, the TTC warning threshold was reduced to 2.5 s. Wang et al. [33] developed different TTC warning thresholds depending on different driving styles. Suzanne et al. [34] divided the conflict zones of lane changes into four levels based on different TTC thresholds.

Due to the complexity and instability of machine learning models [35], they are not maturely used in practical adaptive LCW algorithms. Although numerous self-learning algorithms of driving characteristics based on mathematical optimization methods have been developed to improve the performance and acceptance of longitudinal driver assistance systems (i.e., forward collision warning system) [36], [37], researches focused on the performance improvement of vehicle lateral safety systems (i.e., LCW system) are sparse. In addition, the efficiency and accuracy of existing self-learning algorithms require improvements. In this paper, a self-learning method to determine a driver's lane change characteristics based on signal detection theory (SDT) was proposed. SDT judgment is a process based on a statistical decision. This method is usually used to assess the discriminatory ability of participants between signal and noise using the accuracy, false positive rate, and false negative rate. The TTC and relative distance between the subject vehicle and rear vehicle in the target lane were determined and used as the LCW indicators. By learning the characteristics of the two indicators during lane changes of different drivers, the proposed adaptive algorithm was able to capture the unique lane change characteristics of the drivers and determine the optimal warning thresholds corresponding to the different drivers. In order to verify the effectiveness of the adaptive algorithm, an embedded system platform and a test vehicle platform were developed to conduct a real vehicle test. The remainder of the paper is organized as follows. The self-learning method of the drivers' lane change characteristics based on the SDT is introduced in Section II. The vehicle verification experiments are presented in Section III. The results and discussions are presented in Section IV. Finally, conclusions are drawn in Section V.

II. ADAPTIVE LCW ALGORITHM DESIGN

The development of the adaptive LCW algorithm includes the selection of the warning indicators, the determination of the warning criteria, learning of the lane change characteristics, and online adjustment of the warning threshold. The different lane change warning criteria intuitively paralleled to different warning indicators and warning thresholds. For the same warning criterion, the personalized characteristics of the different drivers are adequately depicted by the values of the warning indicators. Currently, the performance of the conventional self-learning algorithms of driver lane change characteristics (i.e. neural network, HMM, and GMM) in embedded systems requires further improvement. Hence, we employed SDT method to learn the personalized drivers' lane change characteristics and determine the optimal warning threshold for different drivers.

A. WARNING INDICATOR SELECTION AND WARNING CRITERION ESTABLISHMENT

The selection of the warning indicators is the basis for determining the warning criteria. At present, the following three indicators have been used in LCW systems: the relative distance between the subject vehicle and rear vehicle in the target lane, the required deceleration of the rear vehicle, and the TTC. The relative distance is an important indicator in the gap acceptance lane change model and the minimum safe spacing (i.e., the minimum acceptable relative distance for a lane change) is widely used to assessing lane change safety. The required deceleration of the rear vehicle can be modeled as game behavior between the subject vehicle and rear vehicle during the actual lane changes. However, some of the parameters needed to determine the required deceleration cannot be obtained directly. As the primary warning indicator, the TTC not only represents the influence of the relative distance on the lane change behavior but also takes into account the relative velocity, which has been widely used in various lane change safety models. However, a single indicator is often not sufficient to ensure lane change safety, i.e., a small relative speed will result in a large TTC value. In this study, we used the relative distance as an additional indicator to compensate for the disadvantages of the TTC indicator.

Numerous empirical studies have investigated the effect of different LCW criteria, such as the TTC and relative distance indicators; the warning criteria established by the Bosch company are shown in Table I. In order to determine the matching degree between the existing warning criteria and the driver lane change characteristics, vehicle road tests were conducted in our previous study [38]. During the tests, participants drove the test vehicle (i.e., shown in Fig. 3) in a normal manner on a freeway and extremity moment of lane changes were recorded. When participants pressed the wireless button on the left side of the steering wheel, the extremity moment was confirmed by the participants as the last time the test vehicle could execute a lane change without coming into conflict with the vehicle approaching from the rear in the target lane. The corresponding lane change warning indicator values at the extremity moment can be derived based on the collected parameters (i.e., test vehicle speed, target vehicle speed, relative distance, etc.). The extremity moment indicated the driver's cognition of lane change safety and the difference in extremity moment reflected the individual driving characteristics. In order to improve the acceptance of LCW systems,

TABLE 1. The warning criteria formulated by the BOSCH company.

Relative Distance	3-25 m	25-45 m	45-75 m
TTC warning threshold	2.5 s	3.0 s	3.5 s

the warning threshold should keep consistent with driver's subjective cognition of lane change safety. A comparison of the relative distance between the subjective safety cognition and the existing warning criteria are depicted in Fig. 1. The blue marks indicate the responses of the individual drivers. The gray area denotes the warning interval resulting from the existing warning criteria. The blue marks located in the gray area denote instances in which the existing warning criterion captured the drivers' lane change characteristics and was consistent with the safety cognition of the driver. However, approximately 60% of the data are outside of the gray area, indicating that the existing warning criteria does not conform to the drivers' cognition of lane change safety.

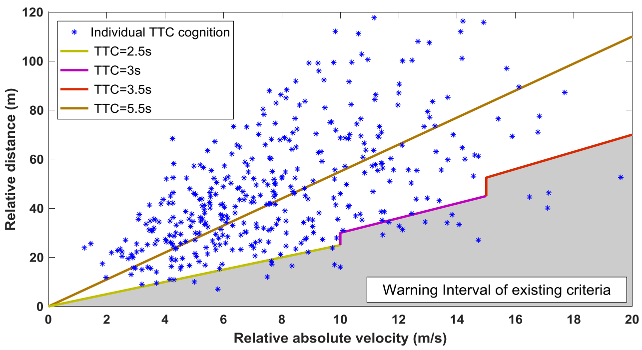

FIGURE 1. Comparisons of the relative distance for existing warning criteria and drivers' lane change safety cognition.

In order to establish a warning criterion that could capture the majority of drivers' lane change characteristics, we modified the existing warning criteria based on empirical researches. The modified warning criterion was divided into two parts depending on the speed of the subject vehicle. When the subject vehicle speed ranged between 40 km/h and 80 km/h, the warning criterion in the low-speed range was activated. The definition of warning thresholds under this criterion was that the longitudinal relative distance between the subject vehicle and rear vehicle in the target lane reached 4 m or the longitudinal relative distance reached 19 m with a TTC value reached 3 s. When these thresholds were reached, a warning was transmitted to the drivers. The warning criterion in the high-speed range was triggered when the subject vehicle speed was greater than 80 km/h. The definition of warning thresholds under this criterion was that the longitudinal relative distance between the subject vehicle and rear vehicle in the target lane reached 5 m or the longitudinal relative distance reached 20 m with a TTC value reached 3 s.

B. SELF-LEARNING ALGORITHM BASED ON SDT

SDT is originally developed in psychology researches [39]. Psychologists determined that human perception can be regarded as comprehensive information processing, i.e., the perceived information represents the signal and the random factors during human perception represent noise [40]. The process of information identification by participants is considered a process of signal recognition and elimination of noise. In a system containing both signal and noise, the SDT method can be used to evaluate the discrimination ability of participants between signal and noise. In psychological experiments, SDT is usually used to test the characteristics of participants and their response to signals. Actually, SDT judgment is a process of statistical decision. The participants characteristics are evaluated based on the detection of H_0 (Noise), and H_1 (Signal). As shown in Table 2, there are four possible outcomes of signal identification, namely hit, false positive, false negative, and correct rejection. When a signal is identified as noise by the participant, the outcome is labeled as a false negative and if a noise is identified as a signal, the outcome is labeled as a false positive. A hit and correct rejection indicate that the signal or noise was correctly identified by the participants.

TABLE 2. SDT judgment matrix.

Participant judgment		Signal	Noise
System reality	Signal	Hit	False negative
	Noise	False positive	Correct rejection

An intelligent LCW system should adapt to different driving styles to achieve the highest accuracy and improve system acceptability. The objective signal and noise based on the SDT method in this study represent the driver completed lane change operation, and driver abandoned lane change operation, respectively. Accordingly, the subjective signal and noise with regard to the LCW criterion represent warning and no warning, respectively. In order to adapt to different drivers, the warning judgment from the LCW system should match the lane change decisions by the participants as much as possible. Hence, the warning threshold should be adaptively adjusted in real-time based on the driver's lane change characteristics. The LCW judgment matrix based on the SDT judgment matrix is presented in Table 3. A false negative means that the driver abandoned a lane change and the LCW system produced no warning. A false positive means that the driver completed a lane change operation and the LCW system still produced a warning. The other two outcomes represent correct warnings.

TABLE 3. The lane change warning judgment matrix based on the SDT judgment matrix.

	System warning	No system warning
Complete lane change	False positive	Correct warning
Abandon lane change	Correct warning	False negative

The accuracy of the LCW system P_r is:

$$P_r = \frac{N_c + N_q - N_w - N_l}{N_c + N_q} \tag{1}$$

The false positive rate of the LCW system P_w is:

$$P_w = N_w / N_c \tag{2}$$

The false negative rate of the LCW system P_l is:

$$P_l = N_l / N_q \tag{3}$$

where N_c represents the number of complete lane change operations, N_q represents the number of yielding lane change operations, N_w represents the number of completed lane change operations with a warning from the LCW system, N_l represents the number of yielding lane change operations with no warning from the LCW system.

In order to easily label the lane change characteristics, we defined the false negative rate P_w and the false positive rate P_l as the aggressive index and conservative index, respectively. The two indices were closely related to the driver's individual lane change characteristics. The higher the aggressive index, the greater the proportion of events was when the driver consistently completed lane changes with LCW system warnings. In this case, the warning was not heeded by the driver and was considered too conservative for the aggressive driver. Similarly, the higher the conservative index, the greater the proportion of events was when the driver decided to abandon lane changes with no warning from the LCW system. The driver was very cautious and although the system regarded the current traffic scenario as safe for lane changes, this behavior was considered too aggressive for the conservative driver. The accuracy P_r reflected the matching degree between the warning criterion and the individual characteristics and was one of the indicators of whether the LCW criterion needed to be revised. The proposed adaptive algorithm automatically determined the optimal warning thresholds according to the values of P_r, P_w, and P_l.

The flow-chart of the self-learning algorithm of the driver lane change characteristics is depicted in Fig. 2. The implementation of the adaptive algorithm consisted of the learning stage and the thresholds fluctuation stage. In the learning stage, the relative parameters of the driver's individual lane changes were recorded and the lane change characteristics were captured using the SDT method. During this phase, each lane change behavior (including completed lane changes and yielding lane changes) was added to the original dataset and the values of P_r, P_w, and P_l were calculated after each lane change operation. The optimal threshold was determined based on the values of P_r, P_w, and P_l, and the selected threshold was exploited to judge the manifestation of the next sample according to Table 2. In addition, the selected threshold was also used as the basis for the following calculations of P_r, P_w, and P_l. Since the purpose of this stage was to learn the driver's lane change characteristics, a warning would not deliver to drivers even when the warning threshold was reached. The learning stage was terminated when the value of P_r reached a predetermined value, which indicated that the warning threshold based on this driver's lane change characteristics had been captured. After the learning stage, the selection of the optimal warning thresholds still followed the steps shown in Fig.2 and we defined this phase as the threshold fluctuation stage. The purpose of this stage was to adapt the warning thresholds according to the driver's state fluctuations regarding lane change characteristics. The filtering steps for the optimal threshold were the same as those in the learning stage. Inversely, the warning was issued to the driver once the warning threshold was reached. Following are the details of the process.

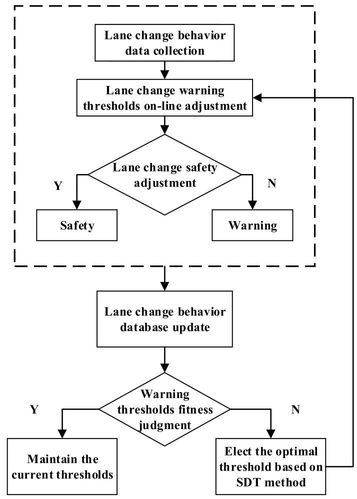

FIGURE 2. Flow-chart of the self-learning algorithm of driver lane change characteristics.

1. Database establishment and updating of lane change behavior. The database was used to capture the information required for self-learning of the drivers' lane change characteristics obtained from the SDT method and the parameters recorded by the database included the TTC value, the relative distance between the subject vehicle and rear vehicle in the target lane, the speed of the subject vehicle, the lane change type (completed or abandoned lane change), and the warning results (whether the system issued a warning).

The lane change sample dataset (including completed lane change and yielding lane change) consisted of 500 data points derived from naturalistic driving experiments in our previous study [41]. During the tests, participants drove the test vehicle (i.e., shown in Fig. 3) in a normal manner on a freeway and the parameters of the lane change were recorded. By analyzing

FIGURE 3. Components of the test platform.

the video of the naturalistic driving experiments, we determined the relevant parameters at the initiation of lane change and at the time of yielding the lane change. Then 350 groups completed and 150 groups abandoned lane change were selected to constitute the original database. The threshold corresponding to an accuracy P_r of 80% was determined as the initial threshold (TTC=3 s). During the learning stage, the new data were added to the original dataset for calculation of P_r, P_w, and P_l. After each calculation, the data point in the original dataset that had the largest error with regard to the optimal threshold would be overwritten by the new data that belonged to the individual. The learning stage was terminated when the accuracy P_r reached 85%. The previous data were not be substituted by the more recent data of the individual during the threshold fluctuation stage.

2. Calculation of the optimal value of the TTC thresholds. According to the SDT method, we determined the adjustment range of the TTC threshold as [0 s, 8 s] and the selection step of the TTC threshold was determined as 0.2 s. The accuracy P_r, the false negative rate P_w, and the false positive rate P_l were calculated for different TTC thresholds according to (1), (2), and (3), respectively. The threshold with the highest accuracy and relatively low false negative rate and false positive rate was selected as the optimal warning threshold.

3. Calculation of the optimal value of the relative distance threshold. Since the warning criterion used in this study consists of an upper limit and lower limit of the relative distance, it was necessary to determine two optimal warning thresholds. The lower limit threshold indicated that an alarm was triggered if the relative distance was less than the set value. The upper limit threshold indicated that an alarm was triggered when both the relative distance and TTC value were less than the set values respectively. According to the warning criterion established in this study, the initial lower limit and upper limit thresholds were determined as 4 m and 19 m in the low-speed range, respectively. Similarly, the initial thresholds in the high-speed range were confirmed as 5 m and 20 m, respectively. For the optimal threshold of the upper limit, we determined the adjustment range of the relative distance as [-5 m, 5 m], which indicated that we would search for the optimal value in the range of [14 m, 24 m] in the low-speed range. For the optimal threshold of the lower limit, we determined the adjustment range of the relative distance as [-4 m, 4 m], which indicated that we would search for the optimal value in the range of [0 m, 8 m] in the low-speed range. The selection step of relative distance threshold was determined as 0.5 m, which indicated that the values of P_r, P_w, and P_l were calculated every 0.5 m. The threshold with the highest accuracy and relatively low false negative rate and false positive rate was selected as the optimal warning threshold.

III. ACTUAL VEHICLE EXPERIMENTS

At present, the research and verification of adaptive LCW algorithms based on driving characteristics are principally conducted using a driving simulator, whereas verification results derived from real vehicle tests are sparse. However, there is a distinct difference between a driver's lane change characteristics in the driving simulator and under normal driving conditions. In addition, the difference in the hardware also affects the verification results of the adaptive algorithm. Therefore, in this study, we established a data collection system and embedded system in a real vehicle to acquire the parameters and execute the adaptive algorithm during the vehicle experiments.

A. TEST PLATFORM

To achieve our research objective of a verification test, a data collection system and embedded system in an ordinary vehicle was exploited. The integrated platform and the instrumentation are shown in Fig. 3. The data collection system included two millimeter-wave radars (one for the front and one for the rear), video monitoring system, GPS, Mobileye system, controller area network (CAN) bus, and industrial computer. The data collection system stored all the parameters while providing the required parameters for the adaptive algorithm (i.e., the TTC value and relative distance between the subject vehicle and rear vehicle during lane changes, the lane change type, and the speed of the subject vehicle). The millimeter-wave radar was used to obtain the relative speed and distance between the subject vehicle and rear vehicle. The video monitoring system was used to record the lane changes. The GPS device provided the geographical positions and speed of the subject vehicle. The Mobileye system provided the distance between the subject vehicle and the lane line. The CAN bus served as the data transmission channel. The industrial computer was used to record the data obtained from the instruments. The embedded system provided a platform for the operation of the adaptive algorithm; the system was implemented as a C application. The sampling frequency of the data collection system and the embedded system was 20 Hz.

B. PARTICIPANTS AND TEST ROUTE

Three experienced drivers were recruited to participate in the experiments. The three male drivers were of similar age (30, 34, and 35 years old) and possessed similar driving experience (5, 6, and 7 years). The participants were physically healthy and none had been involved in a severe traffic accident in the past five years. Before the experiments, the participants were provided an opportunity to perform some trips to become familiar with the test vehicle. In order to obtain as many lane changes as possible, a full closed two-way, 4-lane expressway was selected to perform the experiments. On account of the heavy traffic and a limited number of lanes, more lane changes were recorded than in experiments in a 6-lane expressway. The participants totally completed 50 tests with an average duration of an hour and a half in the city expressway of Xi'an, Shaanxi, China. We notified the participants that the driving data were only used to evaluate our algorithm and would not be used for any other purpose.

C. PROCEDURES

During the whole experiments, the participants were informed of the initial points and destinations; for each lane change, the participants were required to turn on the lane change indicator before the initiation of the lane change, and turn off the lane change indicator when the participants abandoned the lane change. No other instructions and restrictions were imposed on the participants. They could navigate the test vehicle as they saw fit while obeying traffic laws and ensuring driving safety. The relative parameters of the subject vehicle and target vehicle were continuously stored by the data collection system. The trigger of the turn signal indicated that the driver intended to perform a lane change and the values of the TTC and the relative distance between the subject vehicle and rear vehicle were passed on to the adaptive algorithm programmed in the embedded system by the CAN bus. In order to ensure that the driver's lane change behavior was recorded accurately, we needed to determine the precise point when the lane change was initiated. We used the value of the distance between the subject vehicle and lane line obtained from the Mobileye system to supplement the confirmation of the lane change initiation moment. When the turn signal light was triggered and the sustained period of growth of the distance between the subject vehicle and either side lane line exceeded 0.5 s, then the lane change initiation moment was confirmed as 0.5 s before. The corresponding values of the TTC and the relative distance between the subject vehicle and rear vehicle were recorded to reflect the driver's lane change characteristics. In addition, the completed and yielding lane changes were also confirmed by the value of the distance between the subject vehicle and the lane line. A completed lane change was defined as the subject vehicle entering the target lane (the value of the distance between the subject vehicle and either side lane line shifted from negative to positive) and the yielding lane change was defined as the subject vehicle returning to the current lane (the sign of the distance value between the subject vehicle and either side lane line was opposite to the previous value).In this study, a discrete Kalman filter [42] was used to filter the discrete data collected by the sensors. During the experiments, warnings from the adaptive algorithm were not delivered to the drivers. The learning results and the warning threshold adjustment results were recorded in the background.

IV. RESULTS AND DISCUSSION

In order to ensure that the proposed algorithm could accurately capture the driver's lane change characteristics, after the actual vehicle experiments, we statistically analyzed the average TTC values of the participants who had completed lane change and yielded lane change in the learning stage and the fluctuation stage; then we compared the offline statistical results with the optimal thresholds derived from the proposed adaptive algorithm based on the SDT method. The comparative analysis was performed in the learning stage and the threshold fluctuation stage, respectively. The comparison results in the learning stage indicated that the adaptive warning algorithm was capable of capturing the drivers' lane change characteristics to develop an appropriate warning threshold for individual drivers. The comparison results in the threshold fluctuation stage demonstrated that the proposed algorithm was able to determine a suitable warning threshold based on the fluctuations in the behavior of the participants.

A. ONLINE ADJUSTMENT RESULTS

During the learning stage, the adaptive algorithm learned the drivers' characteristics and selected an appropriate warning threshold based on the results of P_r, P_w, and P_l. For participant 1 (P_1), participant 2 (P_2), and participant 3 (P_3), the values of the warning threshold in low-speed region (the subject vehicle speed was greater than 40 km/h and less than 80 km/h) after the learning stage were determined as TTC = 4.0 s, D_1(the upper limit of the relative distance) = 23.5 m, and D_2(the lower limit of the relative distance) = 7.5m; TTC = 3.4 s, D_1 = 21.0 m, and D2 =6.5 m; and TTC = 3.0 s, D_1 = 18.0 m, and D_2 = 5.0 m, respectively. For P_1, P_2, and P_3, at the end of the learning stage, the number of lane change samples was 384, 352, and 415, respectively; the detailed results are shown in Table 4. In the updated sample database (included the original data and the personal data), as shown in Table 3, the lane change manifestation detection results of the three participants after the learning stage are shown in Tables 5, 6, and 7, respectively. It was observed that the adaptive algorithm required a different number of lane change samples to capture the lane change characteristics of the three participants during the learning stage. The small sample size indicated that the participant's driving styles resembled the conventional drivers' styles in the original database.

TABLE 4. The number of lane change samples of the participants in the learning stage.

Participants	Complete lane change	Abandon lane change
p_1	292	92
P_2	276	76
P_3	298	117

TABLE 5. The number of lane change manifestations for p_1.

	System warning	No system warning
Complete lane change	30	342
Abandon lane change	89	39

The values of P_r, P_w, and P_l with different TTC thresholds and the three participants were calculated at the terminational moment of the learning stage; the results are depicted in Figs. 4, 5, and 6. For P_1, the value of P_l continuously decreased with the increase in the TTC threshold value, whereas the value of P_w consecutively increased. The value

TABLE 6. The number of lane change manifestations for p_2.

	System warning	No system warning
Complete lane change	29	345
Abandon lane change	89	37

TABLE 7. The number of lane change manifestations for p_3.

	System warning	No system warning
Complete lane change	32	335
Abandon lane change	92	41

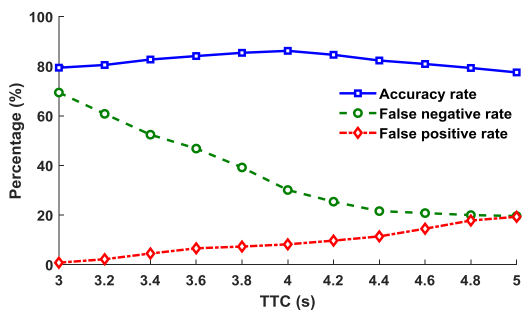

FIGURE 4. The values of P_r, P_w, and P_l with different TTC thresholds for P_1.

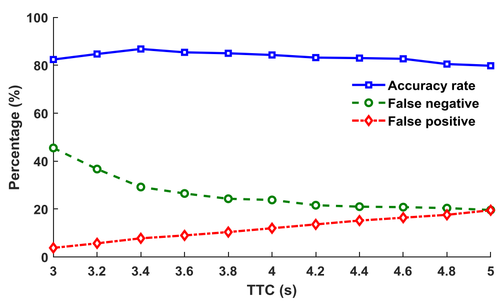

FIGURE 5. The values of P_r, P_w, and P_l with different TTC thresholds for P_2.

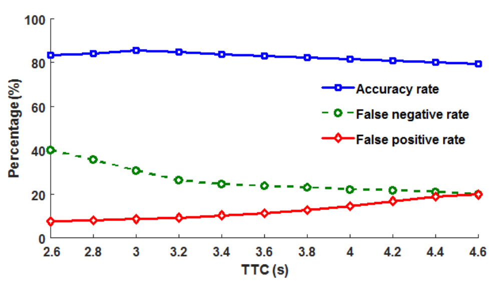

FIGURE 6. The values of P_r, P_w, and P_l with different TTC thresholds for P_3.

slowly increased as the TTC threshold value increased from 3.0 to 4.0 s and then continuously decreased after the threshold reached 4.0 s. The highest value of P_r reached 86.2% at a TTC threshold of 4.0 s and the highest values of Pl and P_w were 30.1%, and 8.2%, respectively. For P_2 and P_3, the trends of P_r, P_l, and P_w were similar to the results of P_1 as shown in Fig. 4. The highest values of P_r were 86.8% and 85.5% with TTC thresholds of 3.4 s and 3.0 s, respectively. The values of P_l and P_w were 29.2% and 7.8% and 30.8% and 8.6%, respectively. P_1 possessed the highest value of P_l of almost 70% at a TTC threshold of 3.0 s, which indicated that P_1 was the most conservative driver among the three participants; and the warning function was regarded as invalid on account of the safer (higher) warning threshold of P_1 than the system's initial value.

Similarly, the values of P_r, P_l, and P_w with different D_1 and D_2 thresholds were calculated at the terminational moment of the learning stage and the results are shown in Figs. 7, 8, and 9. For P_1, P_2, and P_3, The highest values of P_r were 85.7%, 86.4%, and 85.2% with the D_1 thresholds of 23.5 m, 21.0 m, and 18.0 m and the corresponding values of P_l and P_w were 30.2% and 8.8%, 29.3% and 8.1%, and 30.8% and 8.6%, respectively. The highest values of P_r were 85.2%, 85.8%, and 86.1% with the D_2 thresholds of 7.5 m, 6.5 m, and 5.0 m and the corresponding values of P_l and P_w were 32.5% and 9.4%, 28.7% and 8.3%, and 34.8% and 7.6%, respectively. The warning thresholds in the high-speed region (the subject vehicle speed was greater than 80 km/h) were determined according to the calculation results of P_r, P_w, and P_l and the results are shown in Table 8.

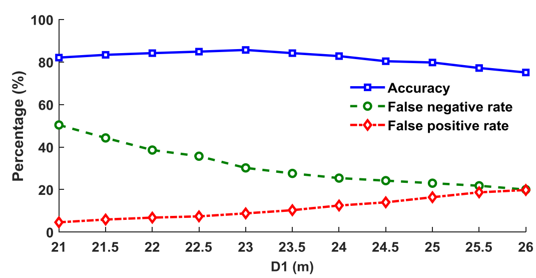

FIGURE 7. The values of P_r, P_w, and P_l with different D_1 thresholds for P_1.

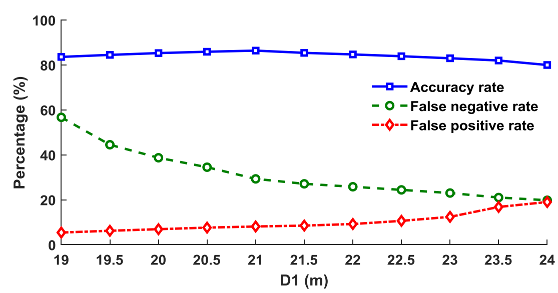

FIGURE 8. The values of P_r, P_w, and P_l with different D_1 thresholds for P_2.

During the threshold fluctuation stage, the original samples would not be replaced by new data and a large number of individual lane changes were recorded in the database. The variability of the individual lane change characteristics would bring about the changes in the values of P_r, P_w, and P_l.

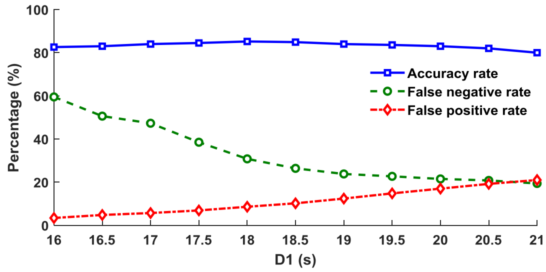

FIGURE 9. The values of P_r, P_w, and P_l with different D_1 thresholds for P_3.

TABLE 8. The warning thresholds for the three participants after the learning stage.

	Low-speed region			High-speed region		
Warning thresholds	TTC	D_1	D_2	TTC	D_1	D_2
P_1	4.0 s	23.5 m	7.5 m	4.2 s	24.0 m	8.0 m
P_2	3.4 s	21.0 m	6.5 m	3.8 s	21.5 m	7.0 m
P_3	3.0s	18.0 m	5.0 m	3.2 s	19.0 m	6.0 m

We defined two threshold adjustment strategies according to the changes in the three values. The decrease in P_r with the increase in P_l (under the same warning threshold) indicated that the current warning threshold was relatively radical (TTC threshold was too low) for certain individuals and the number of yielding lane changes without system warning was high. The decrease in P_r with the increase in P_w (under the same warning threshold) demonstrated that the current warning threshold was relatively conservative (TTC threshold was too high) for certain individuals and the number of completed lane changes with system warning was high. During the experiments, the warning thresholds were adjusted twice in this stage. For P_1, the continuous variation of P_r and P_w were emerged from the 948th to 953th lane change samples. For P_3, the continuous variation of P_r and P_l were emerged from the 1285th to1290th lane change samples. The results before the threshold adjustments are presented in Figs. 10 and 11, respectively. The warning thresholds for P_1 and P_3 were adjusted to TTC $= 3.8$ s, $D_1 = 23.5$ m, and $D_2 = 7.5$ m and TTC $= 3.2$ s, $D_1 = 18.0$ m, and $D_2 = 5.0$ m according to the results of P_r, P_w, and P_l. The results indicated that P_1 became less conservative and P_3 became more conservative.

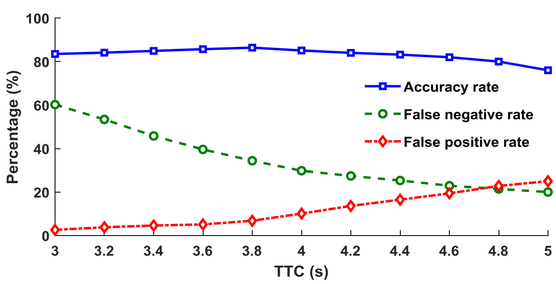

FIGURE 10. The values of P_r, P_w, and P_l with different TTC thresholds for P_1 in the threshold fluctuation stage.

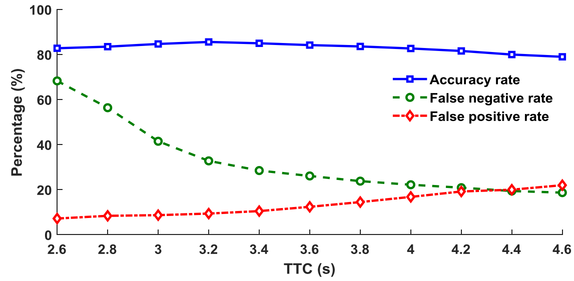

FIGURE 11. The values of P_r, P_w, and P_l with different TTC thresholds for P_3 in the threshold fluctuation stage.

TABLE 9. The TTC statistical results of the different lane changes in the learning stage.

	P_1		P_2		P_3	
	Accomplished	Yielding	Accomplished	Yielding	Accomplished	Yielding
Average	13.127s	4.381 s	10.482 s	3.812 s	8.081 s	3.408 s
Median	10. 1 s	4.2 s	8.2 s	3.4 s	6.8 s	3.1 s
Minimum	3.6 s	3.4 s	3.1 s	2.8 s	2.5 s	2.1 s
Maximum	45.3 s	12.5 s	28.4 s	13.4 s	14.9 s	10.6 s
SD	11.69 s	4.081 s	7.88 s	3.491 s	7.159 s	3.072 s

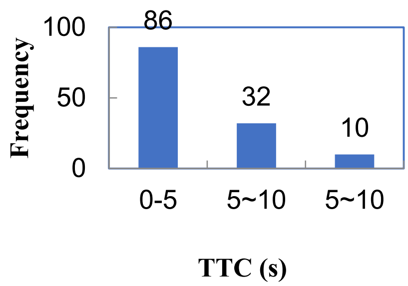

FIGURE 12. Frequency histogram of the TTC of the yielding lane changes for P_1.

B. COMPARISON RESULTS

The offline statistical analysis of the participants' lane change characteristics was conducted in the learning stage and the threshold fluctuation stage. The TTC statistical results for P_1, P_2, and P_3 for the different types of lane changes in the learning stage are shown in Table 9. The average TTC of the completed lane changes of the three participants were 13.127 s, 10.482 s, and 8.081 s, respectively. The average TTC of the yielding lane changes of the three participants were 4.381 s, 3.812 s, and 3.408 s, respectively. In addition, the TTC results of the yielding lane changes were an important factor in the establishment of the TTC warning threshold. The frequency histograms of the TTC of the yielding lane change for the three participants are depicted in Figs. 12, 13, and 14. The results in Table 9 and Figs. 12 to 14 demonstrated that P_1 was the most conservative driver among the three participants; and P_3 was the most aggressive driver. These results were in agreement with the results from the adaptive algorithm and

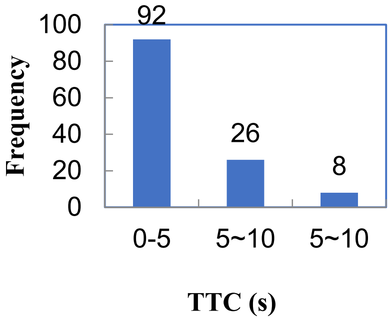

FIGURE 13. Frequency histogram of the TTC of the yielding lane changes for P_2.

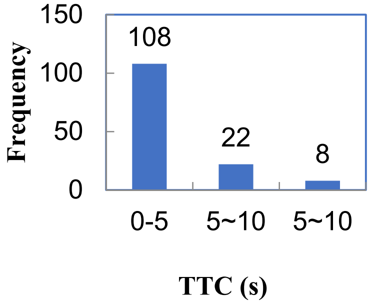

FIGURE 14. Frequency histogram of the TTC of the yielding lane changes for P_3.

the average TTC of the yielding lane change for the three participants were similar to the results for the TTC warning thresholds determined by the adaptive algorithm. The findings indicated that the proposed self-learning algorithm effectively captured the drivers' lane change characteristics and determined an appropriate warning threshold after the learning stage.

The TTC statistical results of the different types of lane changes for P_1 and P_3 in the threshold fluctuation stage (only the fluctuation samples were selected) are shown in Table 10. A comparison of the results shown in Table 10 and Table 8 indicated significant differences in the TTC indicators of completed lane change. The average TTC values of the completed lane changes and yielding lane changes of P_1 were 8.852 s, and 3.849 s, respectively, which indicated that P_1 was less conservative than before. The results for P_3 indicated that this driver was more conservative than before. These results demonstrated that the proposed algorithm was able to adapt to the changes and to determine an appropriate warning threshold.

TABLE 10. The TTC statistical results of the lane changes for p_1 and p_3 in the threshold fluctuation stage.

	P_1		P_3	
	Accomplished	Yielding	Accomplished	Yielding
Average	8.852 s	3.849 s	8.296 s	3.516 s
Median	6.1 s	3.3 s	5.8 s	3.1 s
Minimum	3.0 s	2.8 s	2.8 s	2.6 s
Maximum	15.4 s	11.4 s	14.2 s	12.9 s
SD	7.294 s	3.486 s	6.593 s	3.172 s

V. CONCLUSIONS

The self-learning algorithm for determining individual driving characteristics will improve the acceptance of intelligent systems and enhance the safety of intelligent vehicles. In this study, an adaptive algorithm for determining the LCW threshold based on the drivers' lane change characteristics was established and real vehicle tests with three participants were performed to verify the efficiency and accuracy of the proposed algorithm. Based on the analysis of existing warning criteria, the TTC and the relative distance between the subject vehicle and rear vehicle were used as the warning indicators and the initial warning threshold according to the difference in subject vehicle speed were selected for the adaptive algorithm. In order to capture the drivers' lane change characteristics promptly and accurately, the SDT method was employed to determine the optimal warning threshold and implement an online adjustment of the warning threshold according to the results of the accuracy, false negative rate, and false negative rate. The learning stage and the threshold fluctuation stage were evaluated separately in the adaptive algorithm to capture the lane change characteristics and select the optimal threshold according to the changes in individual behavior.

A test vehicle platform with an embedded system and a data collection system were developed to perform the real vehicle tests. During the learning stage, the optimal warning thresholds in the low-speed region for the three participants were TTC $= 4.0$ s, $D_1 = 23.5$ m, and $D_2 = 7.5$ m; TTC $=$ 3.4 s, $D_1 = 21.0$ m, and $D_2 = 6.5$ m; and TTC $= 3.0$ s, $D_1 = 18.0$ m, and $D_2 = 5.0$ m, while the thresholds in the high-speed region were TTC $= 4.2$ s, $D_1 = 25.5$ m, and $D_2 = 8.5$ m; TTC $= 3.6$ s, $D_1 = 21.0$ m, and $D_2 = 7.0$ m; and TTC $= 3.2$ s, $D_1 = 18.5$ m, and $D_2 = 5.5$ m, respectively. During the threshold fluctuation stage, for P_1 and P_3, the thresholds were ameliorated to TTC $= 3.8$ s, $D_1 = 23.5$ m, and $D_2 = 7.5$ m; and TTC $= 3.2$ s, $D_1 =$ 18.0 m, and $D_2 = 5.0$ m in the low-speed region. The offline results of the lane change characteristics were consistent with the warning thresholds derived from the proposed algorithm, which demonstrated the validity of the adaptive algorithm for learning the drivers' lane change characteristics. In a future study, we will improve the learning efficiency of the adaptive algorithm by identifying the driving styles in advance and considering the specific traffic environments for the confirmation of the warning threshold. In addition, the selected optimal warning threshold can also be useful in microscopic traffic simulation modeling to simulate different styles of lane change behavior.

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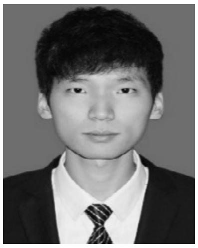

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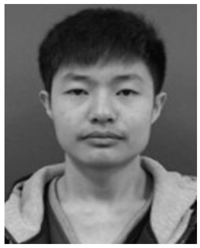

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