Received January 14, 2019, accepted February 3, 2019, date of publication February 21, 2019, date of current version March 12, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2900416

A Novel Lane Change Decision-Making Model of Autonomous Vehicle Based on Support Vector Machine

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This work was supported in part by the National Natural Science Foundation under Grant 51775063 and Grant U1764259, in part by the China Postdoctoral Science Foundation under Grant 2016M602925XB, in part by the Special Funding for Postdoctoral Research Projects in Chongqing, China, under Grant XM2017009, and in part by the Fundamental Research Funds for the Central Universities under Grant 2018CDQYQC0035.

ABSTRACT Autonomous driving is a crucial issue of the automobile industry, and research on lane change is its significant part. Previous works on the autonomous vehicle lane change mainly focused on lane change path planning and path tracking, but autonomous vehicle lane change decision making is rarely mentioned. Therefore, this paper establishes an autonomous lane change decision-making model based on benefit, safety, and tolerance by analyzing the factors of the autonomous vehicle lane change. Then, because of the multi-parameter and non-linearity of the autonomous lane change decision-making process, a support vector machine (SVM) algorithm with the Bayesian parameters optimization is adopted to solve this problem. Finally, we compare a lane change model based on rules with the proposed SVM model in the test set, and results illustrate that the SVM model performs better than the rule-based lane change model. Moreover, the real car experiment is carried out to verify the effectiveness of the decision model.

INDEX TERMS Autonomous vehicle, lane change decision making, support vector machine, Bayesian optimization, drivers' habits.

I. INTRODUCTION

Autonomous driving can change people's lifestyle in the future, and it can improve the utilization rate of cars, traffic capacity, enhance the mobility of people with mobility difficulties, alleviate driver fatigue, and reduce traffic accidents caused by drivers' fault [1]–[3]. Therefore, its related issues have become hot topics recently, and self-driving cars have attracted great social attention in recent years. Advanced Driving Assistance Systems (ADAS) contain Adaptive Cruise Control (ACC), Autonomous Emergency Braking (AEB), Lane Keep Assistant (LKA) and other features, which can help drivers individually in the longitudinal and lateral directions and can realize low-level autonomous driving. However, lane change maneuver is a complex and potentially dangerous traffic behavior, which involves vehicle longitudinal and lateral coupling control. About 539,000 two-lane traffic accidents occurred every year in the United States [4]. Therefore, this paper focuses on the lane change analysis.

Conventional lane change researches were mainly about lane change warning system (LCWS) or microscopic traffic simulation. In LCWS, in order to provide safety warning to drivers when lane change operation may occur, some scholars have studied driver's lane change intention recognition. Li *et al.* [5] combined Hidden Markov Model (HMM) and Bayesian Filtering (BF) models and used the HMM model to decompose driving behavior into sub-behavior. Besides, Tang *et al.* [6] proposed an adaptive fuzzy neural network to predict the driver's steering angle. Rehder *et al.* [7] used Bayesian Network (BN) to predict the probability of lane change. In microscopic traffic simulation lane change research, Gipps [8] put forward a set of rules based on six factors: safe gap distances, the location of

The associate editor coordinating the review of this manuscript and approving it for publication was Shunfeng Cheng.

permanent obstructions, existence of transit lanes, the driver's intended turning movement, existence of heavy vehicles, and vehicle speed. Moreover, Kesting *et al.* [9] proposed the rule of Minimizing Overall Braking Induced by Lane Changes (MOBIL), which adopted the parameter of politeness to make lane change behavior more cooperative. Singh and Li [10] used the data of loop detector to estimate the traffic density of frequent lane-change roads and introduced Markov chain to describe lane change behavior in the state space model. Toledo and Katz [11] integrated the invisible Markov model into a switching model, proposed the state-dependent lane change model.

Though research about lane change assistance or microscopic traffic simulation model can be found in many studies, little research about autonomous lane change has been undertaken. Autonomous lane change can be divided into three stages: 1) lane change decision making; 2) trajectory planning; 3) path tracking. Lane-change decision making aims to determine when to implement lane change process. However, present works on autonomous vehicle lane change mainly focused on path planning and path tracking, lane change decision making is rarely mentioned. Luo *et al.* [12] and Yang *et al.* [13] optimized the lane change trajectory by considering the dynamic collision problem in the lane change process. These studies were carried out at the basis of assuming that the lane change decision has been generated, but how the lane change decision is generated was not described in detail. Nilsson *et al.* [14] assumed that autonomous driving was equipped with an autonomous decision-making system in his research on trajectory planning. Balal *et al.* [15] designed a binary decision model for autonomous lane changing based on fuzzy inference system, but it required the driver of the subject vehicle indicates his/her desire to change lane and the selected target lane by turning the vehicle's turn indicator (also known as turn signal). Thus, previous researches on lane change of autonomous driving often assume that lane change decisions have been made or drivers need to show his/her lane change intentions. To the best of our knowledge, seldom studies exist that allows a vehicle to make lane change decision autonomously without the driver's explicit initiation. Vallon *et al*. [16] proposed a lane change initiation method based on SVM, and the SVM algorithm needs to be further studied. Nie *et al*. [17] proposed a decentralized cooperative lane-changing decision-making framework for connected autonomous vehicles to improve the efficiency and stability of traffic.

Moreover, different drivers have different lane change strategies. Sun and Elefteriadou [18] invited 17 drivers to participate in the group discussion and divided them into 4 categories using k-means clustering. Nine scenarios were designed to calculate the possibility of lane change for different types of drivers. Toledo and Katz [11] showed that heterogeneity and state dependence have significant effects on the change behavior. While existing lane change decisions did not consider the habits and characteristics of drivers [19], [20]. The benefits of advanced driver assistance systems can be fully developed only when they meet drivers' requirement [21]. Autonomous lane change will face the same problem before fully unmanned vehicles arrive, so drivers' habits must be considered in lane change strategies.

Therefore, it is necessary to study the safe but learnable autonomous lane change decision making for autonomous vehicles to address the above-mentioned issue. The main contributions of this paper: 1) establish an autonomous lane change decision-making model based on benefits, safety and tolerance, and it shows that the lane change decision is a multi-parametric and nonlinear problem and can provides a basis for feature selection of support vector machine (SVM) model training; 2) propose a SVM model to solve the multi-parametric and nonlinear autonomous lane change decision-making model and it can promise the decision-making model fits the driver's habits. This paper is organized as follows. In section II, the autonomous lane change decision-making model is established through analyzing all impact factors of autonomous lane change. In section III, the SVM algorithm is adopted to address the difficulties due to the multi-parameter and non-linearity of the model. Section IV gives the simulation and experiment result, we compare a rules-based model with our proposed SVM model in the test set, and results show that the SVM model performs much better.

II. ANALYSIS OF AUTONOMOUS VEHICLE LANE CHANGE

Lane change decision is affected by various traffic factors. In order to analyze the decision-making process, an autonomous lane change model is established, which includes one original lane and one target lane. The model can be simplified as shown in figure 1. Where E is the ego vehicle, TP, TR, and P are the preceding vehicle in the target lane, the rear vehicle in the target lane and the preceding vehicle in the original lane, respectively.

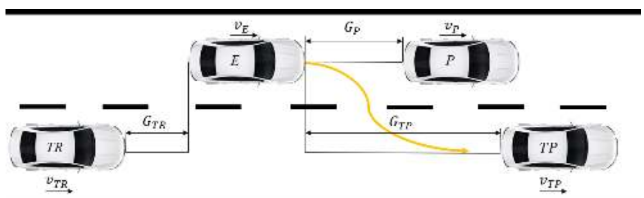

FIGURE 1. Autonomous vehicle lane change model. G_{TR}, G_{TP}, G_P- the longitudinal gap distance between *E* and *TR*, *TP*, *P*;v_E, v_{TR}, v_{TP}, v_P- the longitudinal speed of *E*, *TR*, *TP*, and *P*.

As we all know, lane change decision is influenced by TP, TR, and P. However, how these vehicles influence an autonomous vehicle to abandon the original lane and choose a new lane requires in-depth analysis. This paper will analyze autonomous lane change from three aspects: lane change benefit, safety and tolerance.

A. LANE CHANGE BENEFIT

The purpose of lane change is to improve driving speed or obtain greater space ahead [22]. For autonomous vehicle, the driving speed in the future can be converted into the speed of the preceding vehicle. Thus, the speed benefit can be expressed as

$$v_{\text{benefit}} = \min(v_{\text{set}} - v_P, v_{TP} - v_P) \tag{1}$$

v_{set} represents the speed set by autonomous vehicle. The space ahead can be represented by the relative distance of the preceding vehicle and can be expressed as $G_{TP} - G_P$. The driving benefit model can be established as

$$f_{\text{benefit}} = f(v_{\text{benefit}}, G_{TP} - G_P) \tag{2}$$

B. SAFETY

The safety of lane change is to avoid the collision between the self-driving vehicle and *TR*. Obviously, the greater the gap and relative speed between *E* and *TR* are, the safer the lane change process is. In addition, lane change requires a minimum safe gap. Thus, the following safety model can be established as follows

$$f_{\text{safety}} = \begin{cases} -\infty, & G_{TR} < G_{TR\min} \\ f(G_{TR}, v_E - v_{TR}), & G_{TR} \geq G_{TR\min} \end{cases} \tag{3}$$

$G_{TR\min} > 0$ is the minimum safe gap between *E* and *TR*.

C. TOLERANCE

When the benefit and safety of the lane change process are high enough, the autonomous vehicle may decide to operate lane change with above benefit and safety function, but the distance between *E* and *P* may be pretty large, it might cause frequent lane change of autonomous vehicle if lane change is also decided in this case, Therefore, it is necessary to establish the tolerance model. When *E* is close to *P*, the autonomous vehicle will follow *P* in ACC mode, and the expect distance is determined by the speed and the time headway. Thus, tolerance model can be established as

$$f_{\text{tolerance}} = f(G_P - v_E \cdot t_h) \tag{4}$$

where $t_h > 0$ is the time headway.

D. RULES-BASED MODEL

To establish a simple lane change maneuver, we first assume that the above three models and influencing factors are linear.

$$\begin{cases} f_{\text{benefit}} = a \cdot v_{\text{benefit}} + b(G_{TP} - G_P) \\ f_{\text{tolerance}} = c(G_P - v_E \cdot t_h) \\ f_{safety} = d(G_{TR} - G_{TR\min}) + e(v_E - v_{TR}), \quad G_{TR} \geq G_{TR\min} \end{cases} \tag{5}$$

where a, b, c, d, e are coefficient value.

The rules-based decision-making model can be established as follows

$$\begin{aligned} & \textit{if } f_{\text{safety}} > 0 \textit{ and } f_{\text{benefit}} - \theta f_{\text{tolerance}} > 0 \\ & \quad f_{\text{LC}} = \textit{yes} \\ & \textit{else} \\ & \quad f_{\text{LC}} = \textit{no} \\ & \textit{end} \end{aligned}$$

where θ is weight factor and f_{LC} is lane change decision.

However, autonomous vehicle lane change decision making is a multi-parametric, nonlinear problem, it is difficult to establish a specific mathematical formula model. Thus, the lane change decision-making model of autonomous vehicle should be expressed as

$$f_{\text{LC}} = f(v_{income}, G_{TP} - G_P, G_{TR}, v_E - v_{TR}, G_P - v_E \cdot t_h) \tag{6}$$

The Gaussian kernel SVM is adopted to solve the multi-parametric and nonlinear problem of autonomous lane change decision-making process, and make sure the model fits the driver's habits. The schematic of the proposed method in the paper is showed in figure 2.

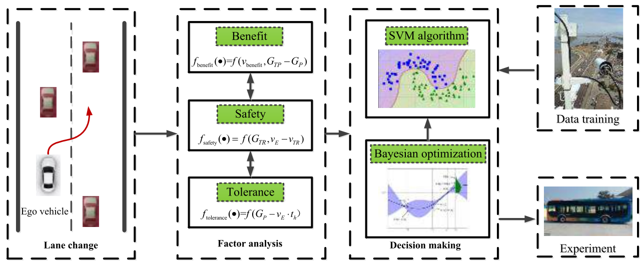

FIGURE 2. Schematic of the proposed method in the paper.

III. DATA EXTRACTION AND SVM MODEL

A. DATA EXTRACTION

Next Generation Simulation (NGSIM) [23] is the most detailed and accurate field data set collected by the Federal Highway Administration (FHWA) for traffic micro-simulation research and development. The vehicle trajectory data is collected by digital cameras, and the precise position of each vehicle on the road segment of 0.5 to 1.0 km is recorded every tenth of a second. It includes real road data such as US 101 in Los Angeles, California, and I-80 interstate in the San Francisco bay area, California. These datasets consist of detailed vehicle trajectory, wide-area detector, and supporting data for researching driver behavior.

According to Balal *et al.* [15], the candidate lane change trajectories can be selected. Generally, vehicles making multiple lane changes are excluded, because that is more like mandatory lane change. The starting point of lane change execution by drivers is usually the starting point of track change, as shown in figure 3. The most accurate method is to calibrate the position of lane change point according to each track. However, such data processing is cumbersome, and it is difficult to obtain large number of lane change data for machine learning model training.

In the first 5 seconds of lane ID change, when the lateral velocity is greater than 0.6096 m/s for the first time, it is taken as the starting point of lane change execution. In order to verify the correctness of the extraction method, 156 groups of lane change points selected manually were compared with the proposed extraction method, and the time error distribution is shown in figure 4. Most of the data are concentrated near the ordinate origin, indicating that the extraction method is

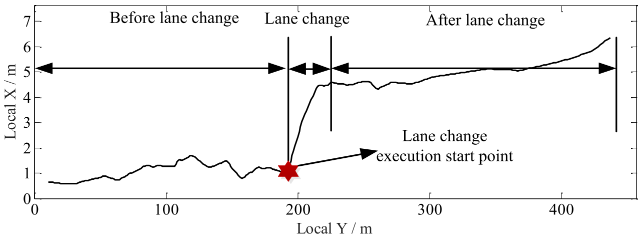

FIGURE 3. Schematic of the proposed method in the paper.

close to manual pick, so this criterion is used to determine the execution point of lane change in data extraction. Only the data before lane change is used for the not change lane data. Compared with other invariant lane data, the data before lane change is close to the lane change environment. Only by distinguishing the choice of lane change conditions of drivers before and after lane change can the autonomous driving decision be more meaningful.

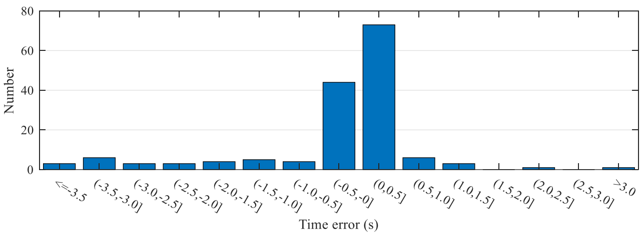

FIGURE 4. Time error distribution.

Among all lane change data extracted, there are some data that the speed and relative distance of *TP* are both decreased compared with *P*. These behaviors are more likely to be mandatory lane changes, so these data have been excluded Finally, 880 lane change data and 1030 counter-examples is got for model training.

B. SVM SOLUTION

The basic theory of SVM is to find a hyperplane in the sample space with the largest margin on training set

$$\begin{cases} D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\} \\ x_i = [v_{income}, G_{TP} - G_P, G_{TR}, v_E - v_{TR}, G_P - v_E \cdot t_h] \\ y_i = \{-1, +1\} \end{cases} \tag{7}$$

The hyperplane is formula (5) and can be expressed as

$$\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x} + \mathrm{b} = 0 \tag{8}$$

where $\boldsymbol{\omega} = (\omega_1; \omega_2; \cdots; \omega_d)$ is the normal vector, which determines the direction of the hyperplane; b is the displacement term, which determines the distance between the hyperplane and the origin of coordinates.

The distance from any point $\boldsymbol{x}$ to the hyperplane can be written as

$$\gamma = \frac{|\boldsymbol{\omega}^T\boldsymbol{x} + b|}{||\boldsymbol{\omega}||} \tag{9}$$

The margin of the SVM is

$$\gamma = \frac{2}{||\boldsymbol{\omega}||} \tag{10}$$

We can solve formula (9) to get the largest margin.

$$\begin{aligned} &\min_{\boldsymbol{\omega}, b} \frac{1}{2}||\boldsymbol{\omega}||^2 \\ &s.t.\ y_i(\boldsymbol{\omega}^T\boldsymbol{x}_i + b) \geq 1, \quad i = 1, 2, \cdots, m \end{aligned} \tag{11}$$

In order to facilitate the solution of the model, it is usually highly efficient to convert formula (9) to dual problem by using Lagrange multiplier method.

$$\begin{aligned} &\max_{\boldsymbol{\alpha}} \sum_{i=1}^{m} \boldsymbol{\alpha}_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \boldsymbol{\alpha}_i\boldsymbol{\alpha}_j y_i y_j \boldsymbol{x}_i^T \boldsymbol{x}_j \\ &s.t. \sum_{i=1}^{m} \boldsymbol{\alpha}_i y_i = 0 \\ &\qquad \boldsymbol{\alpha}_i \geq 0, \quad i = 1, 2 \cdots, m \end{aligned} \tag{12}$$

where $\boldsymbol{\alpha} = (\alpha_1; \alpha_2; \cdots; \alpha_m)$ is the Lagrange multiplier, and formula (10) needs to meet the Karush-Kuhn-Tucker (KKT) conditions.

$$\begin{cases} \alpha_i \geq 0; \\ y_i f(\boldsymbol{x}_i) - 1 \geq 0; \\ \alpha_i(y_i f(\boldsymbol{x}_i) - 1) = 0 \end{cases} \tag{13}$$

The model corresponding to the hyperplane with the largest margin is

$$\begin{aligned} f(\boldsymbol{x}) &= \boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x} + \mathrm{b} \\ &= \sum_{i}^{m} \mathrm{\alpha_i y_i} \boldsymbol{x}_{\mathrm{i}}^T \boldsymbol{x} + b \end{aligned} \tag{14}$$

In real tasks, there may not be hyperplanes in the original sample space that can correctly divide the two types of samples. For this problem, the original space can be mapped to a higher dimensional feature space, and equation (10) can be rewritten as

$$\begin{aligned} &\max_{\boldsymbol{\alpha}} \sum_{i=1}^{m} \boldsymbol{\alpha}_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_i\alpha_j y_i y_j \kappa(\boldsymbol{x}_i,\ \boldsymbol{x}_j) \\ &s.t. \sum_{i=1}^{m} \alpha_i y_i = 0 \\ &\qquad \alpha_i \geq 0, \quad i = 1, 2 \cdots, m \end{aligned} \tag{15}$$

Here $\kappa(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is the kernel function. In this paper, Gaussian kernel function is selected due to its powerful mapping ability, and its expression is as follows

$$\kappa(\boldsymbol{x}_i,\ \boldsymbol{x}_j) = \exp(-\frac{||\boldsymbol{x}_i, \boldsymbol{x}_j||^2}{2\sigma^2}) \tag{16}$$

σ is the bandwidth of the Gaussian kernel. The smaller σ is, the more concentrated the Gaussian distribution is and the easier it is to get overfit, otherwise, the larger is, the easier it is to get underfit.

Thus, formula (12) can be rewritten as

$$\begin{aligned} f(\boldsymbol{x}) &= \boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x} + b \\ &= \sum_{i=1}^{m} \alpha_i y_i \kappa(\boldsymbol{x}, \boldsymbol{x}_{\mathrm{i}}) + b \end{aligned} \tag{17}$$

In real tasks, even if a kernel function is found to make the training set linearly separable in the feature space, it may lead to overfitting, that is, the model is very accurate in the training set but very low in the test set. Soft margin allows support vector machines to make some sample size errors can alleviate this problem. The general form is

$$\min_{f} \ \Omega(f) + C\sum_{i=1}^{m} \ell(f(\boldsymbol{x}_i), y_i) \tag{18}$$

where, $\boldsymbol{\Omega}(f)$ is structure risk, which is used to describe some properties of the model. $\sum \ell(f(\boldsymbol{x}_i), y_i)$ is called empirical risk, which is used to describe the compatibility between the model and data. $C > 0$ is a constant. The smaller C is, the lower the complexity of the model will be, but the lower the fit degree with data will be, which is easy to be underfitted. The larger C is, the greater the complexity of the model is, the higher the fit degree with data is, and the easier the overfitting is. By using hinge loss, the optimization goals in formula (9) can be rewritten as

$$\min_{\boldsymbol{\omega}, b} \ \frac{1}{2}||\boldsymbol{\omega}||^2 + C\sum_{i=1}^{m} \max(0, 1 - y_i(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{x}_i + b)) \tag{19}$$

Introduce the slack variables ξ_i to represent the empirical risk.

$$\min_{\boldsymbol{\omega}, b} \ \frac{1}{2}||\boldsymbol{\omega}||^2 + C\sum_{i=1}^{m} \xi_i \tag{20}$$

The formula (13) can be rewritten as

$$\begin{aligned} &\max_{\boldsymbol{\alpha}} \ \sum_{i=1}^{m} \alpha_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \alpha_i \alpha_j y_i y_j \kappa(\boldsymbol{x}_i, \boldsymbol{x}_j) \\ &s.t. \ \sum_{i=1}^{m} \alpha_i y_i = 0 \\ &\qquad 0 \le \alpha_i \le C, \quad i = 1, 2 \cdots, m \end{aligned} \tag{21}$$

The formula (19) still needs to satisfy the KKT condition

$$\begin{cases} \alpha_i \ge 0; \\ y_i f(\boldsymbol{x}_i) - 1 + \xi_i \ge 0; \\ \alpha_i (y_i f(\boldsymbol{x}_i) - 1 + \xi_i) = 0 \\ \xi_i \ge 0, \ \mu_i \xi_i = 0 \end{cases} \tag{22}$$

$\mu_i \ge 0$ is the Lagrange multiplier.

C. BAYESIAN OPTIMIZATION ALGORITHM

As can be seen from the above, the effect of SVM is closely related to the value of C and σ, so it is necessary to optimize these two parameters. The Bayesian optimization algorithm (BOA) attempts to minimize a scalar objective function $f(\boldsymbol{x})$ for $\boldsymbol{x}$ in a bounded domain can help to find the best C and σ. Compared with traditional grid search, BOA can improve the efficiency of parameter optimization. The error rate of cross-validation $f(C, \sigma)$ is taken as the objective function, assume $f(C, \sigma)$ obeys Gaussian process.

$$f(\boldsymbol{x}) \sim GP(E(x), K(x, x')), \quad \boldsymbol{x} = [C, \sigma] \tag{23}$$

Acquisition functions are adopted to calculate the maximum expected improvement to find the next fetching $\boldsymbol{x} = [C, \sigma]$ through Bayesian posterior probability.

$$EI(x, Q) = E_Q[\max(0, \mu_Q(x_{best}) - f(x))] \tag{24}$$

x_{best} is the current best point, that is, the point with the lowest error rate of cross-validation, $\mu_Q(x_{best})$ is the error rate of cross-validation at the current best point, and $EI(x, Q)$ is expected improvement.

The algorithm runs as the following steps:

1) Evaluate $f(\boldsymbol{x})$ for a random point $\boldsymbol{x}_1$ in the variable bounds;

2) Update the Gaussian process model of $f(\boldsymbol{x})$ to obtain a posterior distribution over functions Q;

3) Find the new point $\boldsymbol{x}_i$ that maximizes the acquisition function $EI(x, Q)$;

4) Evaluate $f(\boldsymbol{x})$ for $\boldsymbol{x}_i$ and repeat this program until it stops.

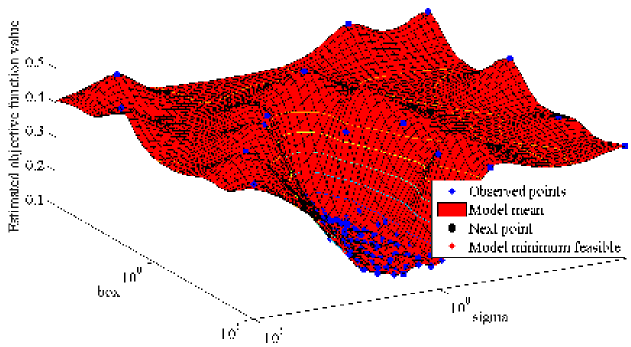

FIGURE 5. Distribution of objective function.

IV. RESULTS

We get the best value that $C = 5.2004$, $\sigma = 1.6581$ after 100 iterations. As shown in figure 6, the minimum cross-validation error has a lot to do with C and σ, and can reach 14.17% with iterations. Results of this analysis are shown in figure 5 and figure 6.

The accuracy of each model is presented in table 1. We compare various SVM models with different kernel functions. Gaussian kernel has the best performance due to its strong mapping ability. Compared with the linear kernel function, Gaussian kernel function can improve the accuracy of

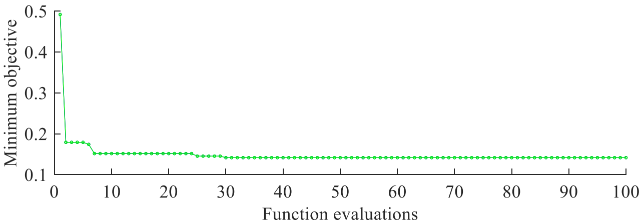

FIGURE 6. Minimum objective function after 100 iteration.

TABLE 1. Accuracy of prediction in different algorithm.

Algorithm	Accuracy			
	Training Set	Test Set	True Positive	False Negative
Linear SVM	75.34%	71.08%	68.34%	73.61%
Polynomial SVM	82.96%	81.20%	79.90%	82.41%
Gaussian SVM	83.15%	84.34%	88.44%	80.56%
BOA Gaussian SVM	85.33%	86.27%	87.43%	86.27%
Rules-based	75.53%	73.73%	61.31%	85.19%

FIGURE 7. Test vehicle.

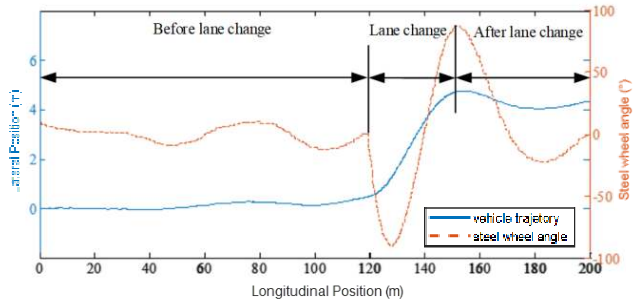

FIGURE 8. Vehicle trajectory and steel wheel angle.

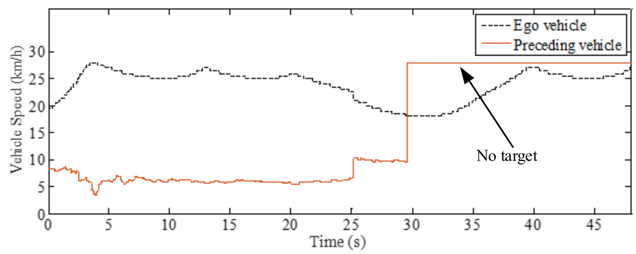

FIGURE 9. Vehicle trajectory and steel wheel angle.

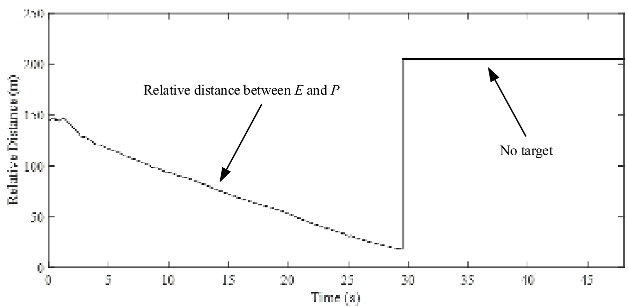

FIGURE 10. Relative distance.

7.61% in the training set and 13.26% in the test set. The accuracy of the BOA optimized Gaussian kernel support vector machine model (BOA Gaussian SVM) is improved with 85.33% in training set and 86.27% in test set. Rules-based models also perform well, with more than 70% accuracy. It should be noted that because it is real data, there still exist many impurities in the data, so it is a great achievement to have this accuracy.

The accuracy of true positive and false negative in the test set of rules-based model is significantly different, with the accuracy of true positive being only 61.31% and False negative being 85.19%. It shows that the rules-based model is too cautious about lane change decision and cannot reflect the real drivers' habit of lane change decision. The BOA Gaussian SVM model has a relatively close accuracy of true positive and false negative (87.43% and 86.27%, respectively), which shows that it can reflect decision-making habits of drivers, greatly.

In order to verify the effectiveness of BOA Gaussian SVM model, we carry out vehicle verification. The test vehicle used in the experiment is Zhongtong bus, whose model is LCK6105GZ. It is equipped with Mobileye, millimeter wave radar, mobile station GPS, AutoBox dSPACE, inertial navigation unit and other devices, as shown in figure 7.

During the process of experiment, the target lane is empty, since information of the vehicle in target lane is difficult to be accurately obtained by the test vehicle. At the beginning of the experiment, the autonomous vehicle travels in a straight line at the target speed of 28 km/h, and the P which is 150 meters ahead of the E travels at a uniform speed of 10 km/h. Experimental results are shown in figure 8, 9 and 10. At the time of 20s, P is 52 meters away from E, and E begins to enter ACC mode and decelerate. At 29.5 s, the vehicle speed reaches 18km/h and the relative distance is 18 m. At this time, the BOA Gaussian SVM lane change decision-making model decides to change lane. Then, the autonomous vehicle changes lane successfully and the vehicle speed gradually rises to the target speed of 28 km/h. When there is no obstacle in front, the target speed v_{set} is set as the speed of P, and the maximum detection range of radar, which is 204.7 meters, is set as gaps between E and P, as shown in figure 9 and 10. The experiment results verifies the correctness and validity of the BOA Gaussian SVM lane change decision-making model.

V. CONCLUSIONS

This paper mainly aims to address the autonomous lane change decision-making problem. Firstly, an autonomous lane change model is established through analyzing the lane change process. We proposed related parameters which impact the autonomous lane change by analyzing lane change benefit, safety and tolerance model. Then, the BOA-Gaussian-SVM-based autonomous lane change decision model is established to solve multi-parameter and nonlinear problem of lane change process. The effectiveness of the proposed model is verified by both simulation and real vehicle tests.

This paper proposes a novel lane change decision-making model, but due to the complexity of real traffic and road condition, the feasibility of the model needs to be further researched.

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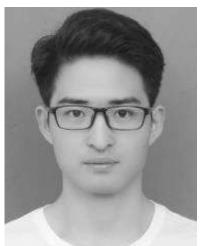

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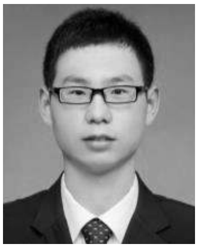

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