IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received June 3, 2020, accepted June 7, 2020, date of publication June 10, 2020, date of current version June 22, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3001306

Research on a Novel Vehicle Rollover Risk Warning Algorithm Based on Support Vector Machine Model

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This work was supported in part by the Teaching Quality and Reform of Higher Vocational Education Project of Guangdong Province under Grant GDJG2019463, in part by the Open Fund Project of the State Key Laboratory of Automotive Simulation and Control under Grant 20160111, in part by the Hebei Provincial High Level Talents Foundation of Hebei Province under Grant A2016002025, in part by the Hebei Province Key Research and Development Project under Grant 17394501D, in part by the Natural Science Foundation of Characteristic Innovation Project of Guangdong Ordinary University and the Science and Technology Research Project of Hebei Higher Education under Grant ZD2017213, and in part by the Subsidized Projects for Overseas Students under Grant CL201705.

ABSTRACT A novel vehicle rollover warning algorithm based on support vector machine (SVM) empirical model is proposed to improve the real-time of un-tripped rollover warning algorithm and accuracy of dynamic rollover warning. Considering the nonlinear characteristic of driver-vehicle-road interaction and the uncertainty of modeling, the traditional deterministic methods cannot meet the requirements of accurate vehicle rollover warning modeling. The probability method considering issues of uncertainty is applied to design vehicle dynamic rollover warning algorithm. The SVM empirical model considers the uncertainties of the driver-vehicle-road system and the real variability of the parameters, provides an explicit function of vehicle rollover safety limit and its gradient, and utilizes the hypersurface visualization boundary to define the rollover safety area and the unsafe area. Targeting on sport utility vehicle under the condition of high-speed emergency obstacle avoidance, simulations are carried out to verify the proposed vehicle rollover warning algorithm based on SVM empirical model and of the simulation results show that the proposed algorithm has accurate warning and good real-time performance. It can effectively improve the warning accuracy of vehicle dynamic rollover, reduce the interference of nonlinear and uncertainty, and significantly improve the active safety performance with vehicle rollover prevention.

INDEX TERMS Rollover warning algorithm, support vector machine, empirical model.

I. INTRODUCTION

The major consequences of traffic accident are the serious loss of life and property, and car rollover accident is one of the most serious traffic accidents. According to statistics, car rollover accidents have become the second most common accidents only after frontal collision [1]. In 2014, although the car rollover accident rate in France was only 4.7%, it caused 14% deaths of all traffic casualties. At the same time, rollover accidents tend to damage public facilities such as roads and bridges, and even caused serious environmental pollution [2].

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

Therefore, the research on vehicle rollover warning and control has received worldwide attention. The research on vehicle rollover warning and control can be classified into two categories: active and passive rollover protection systems. Among them, the active vehicle rollover protection system improves vehicle rollover stability through active control strategy and device [3]–[6]. For example, Li and Liu [7] uses active braking based on predictive control to achieve vehicle rollover stability control, but it involves less non-linear characteristics and uncertainties of the vehicle system. Ghazali *et al.* [8] used front wheel steering and active braking to control vehicle rollover stability. Among them, the former used low-order model prediction to control and track error, while the latter tracked the error through controlling vehicle speed, but they didn't provide the impact of tracking error threshold on rollover control effect. Braghin *et al.* [9] proposed a rollover control strategy based on aerodynamic load estimation. Anubi and Crane [10] used variable stiffness suspension to resist vehicle lateral overturning moment. Zong *et al.* [11] used differential braking and synovial membrane control to control rollover of heavy vehicles, which can effectively improve rollover and yaw stability of heavy vehicles. Dahmani *et al.* [12] used robust controller to control rollover stability under extreme conditions. Jin *et al.* [13] proposed the use of robust control and genetic algorithm for vehicle rollover warning and control. The algorithm has good robustness in vehicle longitudinal centroid position change.

In addition, passive vehicle rollover protection systems, such as rollover warning systems, are often used for rollover control [14]–[19]. For example, Mashadi and Mostaghimi [20] proposed the vehicle dynamics model when the wheels were lifted, and deduced the rollover threshold. Li *et al.* [21] designed an improved predictive LTR (IPLTR) to predict load transfer rate as a rollover warning index. Wang and Chen [22] proposed a method to predict rollover hazard by using the change of centroid position before and after wheel lifting. However, the accuracy of centroid position estimation is difficult to guarantee. He *et al.* [23] proposed using reliability method to carry out rollover early warning control of heavy vehicles. Imine *et al.* [24] used the estimated tire vertical force to calculate the vehicle load transfer rate, and then carried out rollover hazard warning control. Zhu *et al.* [25] proposed an improved Time to Rollover (TTR) method for rollover early warning control of heavy vehicles, in which a Kalman observer was designed to estimate the roll angle of vehicles in real time, thus ensuring the calculation accuracy of load transfer rate LTR and TTR values. Chou and Chu [26] proposed using grey system theory to carry out rollover early warning control of heavy semi-trailer vehicles, in which grey rollover index GRI was used as the basis for rollover risk monitoring.

In summary, most rollover control systems begin to work when the vehicle is going to rollover, and the driver-vehicle-road environment can be regarded as a complex interactive system at that time. The driver or active rollover control device must timely correct the speed and steering of the vehicle according to the vehicle dynamic response and road environment information, so as to avoid the deterioration of vehicle stability.

However, the driver-vehicle-road environment system mentioned above has strong nonlinearity and uncertainty of modeling, and the traditional deterministic scheme is not enough to establish accurate model. A vision-based support vector machine (SVM) steering control algorithm of vehicle is proposed of autonomous navigation, the test result indicates that the algorithm has better accuracy and robustness [27]. Zhu *et al.* [28] proposed a new dynamic driving condition identification method. K-Means algorithm, used to set up the rollover threshold value and Baum-Welch algorithm for optimizing the proposed rollover warning model. The driving pattern recognition (DPR) uses cluster analysis to classify driving cycles into different patterns according to the features extracted from the historical driving data sampling window and utilizes pattern recognition to identify real-time driving patterns. [29]. Yan *et al.* [30] proposed a k-MPSO clustering algorithm for the construction of typical driving cycles. Zhang *et al.* [31] proposed a front vehicle detection algorithm for intelligent vehicle based on SVM method. The experimental results show that the approach can improve the recognition rate and the robustness of preceding vehicle detection for the intelligent vehicle. As mentioned above, SVM is a novel learning method with a theoretical basis and suitable for small samples. It basically does not involve probability measure and law of large numbers, and also simplifies the usual classification and regression problems.

Therefore, it is suggested that the probabilistic algorithm considering uncertainties be applied to the design of vehicle dynamic rollover warning algorithm to reduce the strong nonlinearity of the system and uncertainties of the external interference and effectively improve the accuracy of vehicle dynamic rollover warning.

The novelty of this study is to develop a vehicle rollover warning method considering the uncertainty of driver-vehicle-road environment, in which the system uncertainty is modeled by random variables and whether it exceeds the critical value to assess the risk of vehicle rollover. At the same time, due to the real-time requirement of calculation, it is necessary to determine the most relevant vehicle parameters as random variables in this paper.

In addition, the traditional vehicle rollover prediction index LTR can only be calculated by solving coupled dynamic equation, and cannot be expressed by explicit function. In this paper, support vector machine (SVM) theory is used to design empirical model, which can provide an explicit function of rollover safety limit and its gradient. At the same time, the visual hypersurface is used to define the safe and unsafe areas of vehicle rollover, which further reveals the characteristics of vehicle rollover. The simulation results verify the correctness of the model and algorithm.

The rest of the paper is organized as follows: vehicle model and rollover risk assessment indicator are developed in Section 2. Section 3 focuses on the empirical model of support vector machine. The influence of parameters of SVM model on rollover prediction results are presented in Section 4. Finally, the conclusions are given in Section 5.

II. VEHICLE MODEL AND ROLLOVER RISK ASSESSMENT INDICATOR

A. VEHICLE MODEL

In this research, a 3 degree of freedom (DOF) linear vehicle model is used to design rollover early warning controller. As shown in Figure 1, the 3-DOF vehicle model includes roll, yaw and lateral motion. The following assumptions are made:

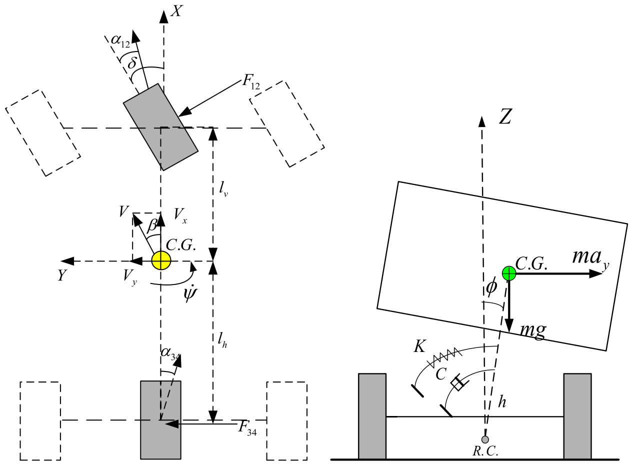

FIGURE 1. **Schematic diagram of simplified 3-DOF vehicle model.**

(1) The model uses the front wheel steer angle as input;
(2) The vertical motion of vehicle is neglected;
(3) The pitching motion of the vehicle is neglected;
(4) The role of aerodynamics is neglected;
(5) The influence of load transfer on the characteristics of tire is neglected;

According to the Darambers principle, three equilibrium equations can be derived as the following.

The moment balance equation around axis Z is

$$J_{zz}\ddot{\psi} = F_{12}l_v - F_{34}l_h \tag{1}$$

The force balance equation in Y direction is

$$m(\dot{V}_y + \dot{\psi}V_x) = F_{12} + F_{34} \tag{2}$$

The moment balance equation around axis X is

$$J_{xeq}\ddot{\phi} = ma_y h\cos\phi + mgh\sin\phi - k\phi - c\dot{\phi} \tag{3}$$

where, m is the mass of the whole vehicle, J_{xeq} is the rotating inertia of the vehicle mass around the roll axis, and J_{zz} is the rotating inertia of the vehicle mass around the Z axis. l_v is the distance from the center of gravity to the front axle; l_h is the distance from the center of gravity to the rear axle; a_y is the lateral acceleration of the vehicle; ψ is the side slip angle of the vehicle; ϕ is the roll angle of the vehicle; v_x, v_y are the longitudinal and lateral speed of the vehicle; F_{12} and F_{34} are the lateral force of the front and rear tires of the vehicle is defined as sum; α_{12} and α_{34} are the roll angle of the front and rear tires; k is the cornering stiffness of the suspension; c is the damping coefficient of the suspension. At the same time, the following conditions are satisfied

$$F_{12} = C_v\alpha_{12} \tag{4}$$

$$F_{34} = C_h\alpha_{34} \tag{5}$$

$$J_{xeq} = J_{xx} + mh^2 \tag{6}$$

where J_{xx} is the rotating inertia of vehicle mass around longitudinal axis of vehicle body center of gravity; C_v and C_h are the cornering stiffness of the front and rear tires respectively. And h is the distance from the center of gravity to the roll center;

With small angle assumption, it satisfies the following formula.

$$a_y = \dot{V}_y + V_x\dot{\psi} \tag{7}$$

$$\alpha_{12} = \delta - \beta - \frac{l_v}{V_x}\dot{\psi} \tag{8}$$

$$\alpha_{34} = -\beta + \frac{l_h}{V_x}\dot{\psi} \tag{9}$$

The motion differential equation of the simplified 3-DOF vehicle model is obtained and written in the form of state equation.

$$\dot{\beta} = -\frac{\sigma J_{xeq}}{mJ_{xx}V_x}\beta + \left(\frac{\rho J_{xeq}}{mJ_{xx}V_x^2} - 1\right)\dot{\psi} - \frac{hc}{J_{xx}V_x}\dot{\phi} + \frac{h(mgh-k)}{J_{xx}V_x}\phi + \frac{C_vJ_{xeq}}{mJ_{xx}V_x}\delta \tag{10}$$

$$\ddot{\psi} = \frac{\rho}{J_{zz}}\beta - \frac{\kappa}{J_{zz}V_x}\dot{\psi} + \frac{C_vl_v}{J_{zz}}\delta \tag{11}$$

$$\ddot{\phi} = -\frac{h\sigma}{J_{xeq}}\beta + \frac{h\rho}{J_{xeq}V_x}\dot{\psi} - \frac{c}{J_{xeq}}\dot{\phi} + \frac{mgh-k}{J_{xeq}}\phi + \frac{hC_v}{J_{xeq}}\delta \tag{12}$$

where it defines

$$\begin{cases} \sigma = C_v + C_h \\ \rho = C_hl_h - C_vl_v \\ \kappa = C_vl_v^2 + C_hl_h^2 \end{cases} \tag{13}$$

B. ROLLOVER RISK ASSESSMENT INDICATOR

Tsourapas *et al.* [32] proposed an algorithm for rollover hazard criterion based on actual vehicle lateral load transfer rate. The roll stability of vehicles can be dynamically reflected by the Load Transfer Ratio (LTR). LTR is simply defined as the ratio of the difference of the vertical loads on the wheels on both sides of the vehicle to the sum of the vertical loads in Equation (14) as below.

$$LTR = \frac{\left|\sum_{i=1}^{n}(FL_i - FR_i)\right|}{\sum_{i=1}^{n}(FL_i + FR_i)} \tag{14}$$

where FL_i and FR_i are the vertical loads on the left and right wheels of the vehicle respectively, and i and n are the position of the axle and the total number of axles respectively.

Miege [33] proposed a set of algorithm for load transfer rate which can be used to control roll stability on test vehicle. LTR can be rewritten as follows,

$$LTR = \frac{a_y}{g}\left(\frac{h + h_{RC}}{d_t}\right) - \frac{h}{d_t}\phi \tag{15}$$

where h is the distance from the center of mass to the center of roll; h_{RC} is the height of the roll center; d_t is the vehicle tread; a_y is the lateral acceleration at the center of gravity; and ϕ is the roll angle of the spring-loaded mass of the vehicle.

In summary, LTR is a value that varies between [−1, 1], and LTR is 0 when vehicles are driving on straight roads. In extreme conditions, when one side of the axle is lifted off the ground, the LTR is −1 or 1.

In this study, the rollover risk assessment index is defined as the rollover limit state function $R(x)$. The index can effectively define the safety boundary of rollover hazard, that is, in the dangerous area of rollover, the function value is positive; in the safe area, the function value is negative. Specific definitions are as follows,

$$R(x) = |LTR_{\max}(x)| - LTR_{threshold} \tag{16}$$

where $LTR_{threshold}$ is the preset threshold of the lateral load transfer rate, and $LTR_{max}(x)$ is the maximum value of lateral load transfer rate in the process of vehicle rollover hazard prediction. x is an n-dimensional random variable with all the parameters affecting rollover stability.

A lot of research work has been carried out to determine the key vehicle condition and parameters involved in roll over. One finding [34] is that, with other vehicle parameters unchanged, vehicle height of mass center, vehicle longitudinal speed, tire lateral stiffness and track of vehicle are, in turn, the most influential factors in vehicle rollover stability. Because the larger the dimension of random variables is, the more the calculation work of subsequent rollover hazard prediction are involved, which affects the real-time performance of the algorithm. Therefore, the two parameters including vehicle height of mass center and vehicle longitudinal speed are selected in this paper as two-dimensional random variables for the follow-up processing of rollover warning.

III. EMPIRICAL MODEL OF SUPPORT VECTOR MACHINE

A. SVM ALGORITHM

Support vector machine (SVM) was first proposed by Vapnik *et al.* in 1998 [35]. It has many unique advantages in solving small samples, nonlinearity and high-dimensional pattern recognition. Support vector machine (SVM) is based on the Vapnik-Chervonenkis (VC) dimension theory of statistical learning theory and the principle of structural risk minimization, seeking the best compromise between the complexities of the model and learning ability according to the limited sample information. The idea of support vector machine classification model is based on the principle of structured risk minimization which makes it different from traditional neural network model. SVM model seeks to minimize the upper bound of generalization error rather than empirical error. As SVM algorithm has strong nonlinear classification ability and can be used for classification and regression, especially as a better classification tool, it has been widely used in pattern recognition and other fields.

Two-class support vector machine algorithm is used in this research. Two types of training samples are unsafe and safe zones. The optimal classification surface of SVM requires that the classification line not only separates the two types of training samples correctly, that is, the training error rate is 0, but also maximizes the classification interval (margin). As shown in Figure 2, H is the classification line that separates the two types of samples, H_1 and H_2 from the two samples are the points closest to H and parallel to H, and the margin is the vertical distance between H_1 and H_2. The red and blue points in the graph are support vectors, which are also the points closest to the optimal classification surface.

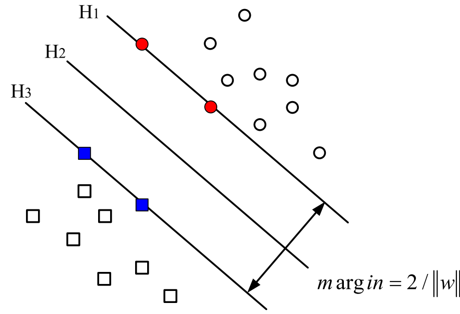

FIGURE 2. Optimal classification surface of SVM.

The two-class support vector machine algorithm is as follows: the training data set is $(x_1, y_1), \ldots, (x_n, y_n)$, x∈Rn, y∈{+1, −1}. The linear discriminant function is,

$$g(x) = (w^T x) + b \tag{17}$$

where, in this paper, the training data x is the data of longitudinal speed and height of mass center; y is class tag, $y_n \in \{-1, 1\}$; w is normal vector of hyperplane. The discriminant function is normalized to make that all the samples of the two classes to satisfy the condition $|g(x)| \geq 1$. When $y = -1$, $g(x) \leq -1$; When $y=1$, $g(x) \geq 1$. In which the sample closest from the classification plane is when is $|g(x)| = 1$.

The objective of this study is to find the decision-making surface with the largest classification interval. Firstly, the margin classification interval needs to be figured out. Because the nearest sample from the classification surface satisfies $|g(x)| = 1$, the margin classification interval is defined as (18).

$$m\arg in = \frac{2}{\|w\|} \tag{18}$$

where, $m\arg in$ is the maximum value of distance from any sample point to hyperplane. So the optimal classification surface problem can be expressed as the following optimization problem,

$$\begin{cases} \min & \dfrac{1}{2}\|w\|^2 + C\displaystyle\sum_{i=1}^{n}\xi_i \\ y_i[(w^T x) + b] \geq 1 - \xi_i, & i = 1, 2, \cdots, n \end{cases} \tag{19}$$

where, ξ_i is classification loss for the ith sample point. In order to consider the generalization performance of the algorithm. b is the solution of the above problem.The penalty factor C is used to control the training error of the system. High values of C favors the separation between the two domains but make this separator sensitive to data noise.

If there are errors on the system, less values of C are suggested. This can lead to give less influence of the uncertainties and reduce the number of support vectors.

The above optimization problem is a typical conditional extremum problem, which can be solved by Lagrange multiplier method as follows,

$$L(w, b, a) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{n} a_i[y_i(w^T x + b) - 1] \quad (20)$$

where, a_i is Lagrange coefficient; partial derivative of Lagrange function is obtained and make it equal to zero.

$$\begin{cases} w^* = \sum a_i y_i x_i \\ \sum_{i=1}^{n} a_i y_i = 0 \end{cases} \quad (21)$$

By introducing the optimal solution of L, we can get the optimal solution.

$$L(w^*, b^*, a) = -\frac{1}{2}\sum_i \sum_j a_i a_j y_i y_j (x_i, x_j) + \sum_i a_i \quad (22)$$

To satisfy the optimum solution w^* and b^* need to satisfy the following,

$$\sum_{i=1}^{n} a_i(y_i[(w^T x) + b] - 1) = 0 \quad (23)$$

For most samples, they are not on the nearest line to the classification surfaces, that is when $y_i[(w^T x) + b] - 1 > 0$, $a_i = 0$; Only a few data points (support vectors) on the boundary satisfy,

$$\begin{aligned} y_i[(w^T x) + b] - 1 &= 0 \\ a_i &\neq 0 \end{aligned} \quad (24)$$

B. EXPLICIT FUNCTION OF ROLLOVER LIMIT STATE FUNCTION

Support vector is only a small part of the whole samples, which greatly reduces the computational complexity involved in the original problem. Finally, the optimal classification function (explicit function of limit state function) of the above problem is obtained.

$$R(x) = sgn\left\{(w^*.x) + b^*\right\} = sgn\left\{\sum a_i y_i (x_i.x) + b^*\right\} \quad (25)$$

where $sgn()$ is a sign function. Since the non-support vectors correspond to $a_i = 0$, the summation of the above formulas is actually only for support vectors.

For nonlinear problems, SVM tries to transform them into linear problems in another space by means of nonlinear transformation which can be realized by defining proper inner product function (kernel function). At present, the commonly used kernel functions include polynomial kernel, radial basis function kernel and sigmoid kernel and etc., and the selection of their parameters has a great impact on the final identification results [36]. The optimal classification function (explicit function of limit state function) corresponding to the kernel function can be expressed as follows,

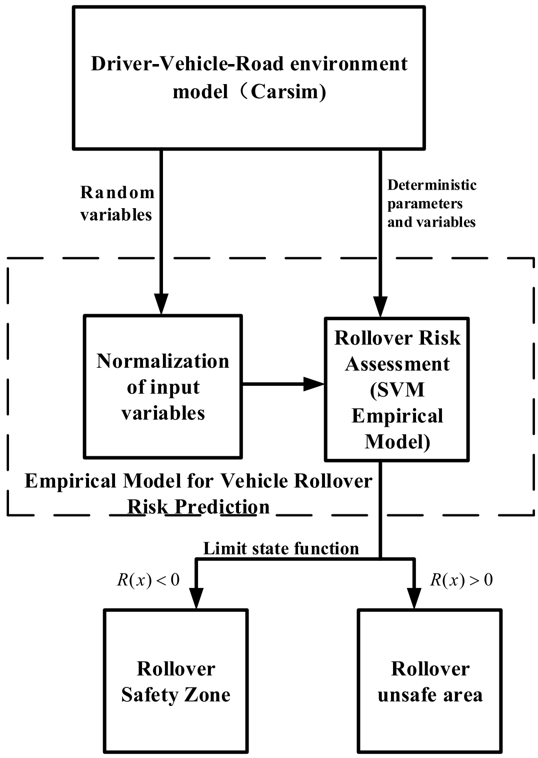

FIGURE 3. An empirical model of vehicle rollover prediction based on SVM.

$$R(x) = sgn\left\{\sum a_i y_i K(x, x_i) + b^*\right\} \quad (26)$$

C. EMPIRICAL MODEL OF VEHICLE ROLLOVER HAZARD

An empirical model for vehicle rollover hazard prediction is built using SVM algorithm. The essence of the empirical model is a two-class support vector machine classifier, which determines the explicit function of vehicle rollover limit state function. That is, a hypersurface is defined to approximate as much as possible the separating surface between vehicle rollover hazard area and safety area, and continuously divide the vehicle state samples into two different areas: rollover unsafe area ($R(x) > 0$: unsafe)and rollover safe area $R(x) < 0$: safe). The empirical model is shown in Figure 3.

As shown in Figure 3, the driver-vehicle-road environment model in Carsim software is selected to obtain vehicle states and parameters, and two kinds of variables (deterministic variable and random variable) are used as inputs of the empirical model for vehicle rollover hazard prediction. Among them, the random variables include the height of mass center and the longitudinal speed which are most closely related to vehicle rollover. After normalizing the input variables, the SVM classification algorithm is used to determine the sign of rollover limit state function, and the hypersurface is used to visually define the safety and unsafe areas of vehicle rollover. After trained by a large number of off-line training

FIGURE 4. Carsim SUV rollover warning simulation.

TABLE 1. Vehicle parameters of SUV model.

Vehicle parameters	Values
The track of vehicle	1575 mm
Wheelbase	2630 mm
Vehicle Length	4653 mm
Vehicle width	1785 mm
Vehicle height	1770 mm
Vehicle mass	1990 kg

samples, the empirical model of vehicle rollover prediction based on SVM can be used for on-line rollover warning control of vehicle rollover status.

IV. THE INFLUENCE OF PARAMETERS OF SVM MODEL ON ROLLOVER PREDICTION RESULTS

In order to verify the above-mentioned vehicle rollover hazard prediction model, the rollover warning simulation analysis of a SUV sport utility vehicle under fishhook working condition is carried out in Carsim, the vehicle simulation software of American Mechanical Simulation Company. Carsim SUV rollover warning Simulation sketch is shown in Figure 4.

The main parameters of SUV vehicle model are listed in Table 1.

In this paper, the fish-hook test of National Highway Traffic Safety Administration (NHTSA) is used to evaluate the validity of the empirical model of SVM rollover prediction for a SUV vehicle. The initial speed of the vehicle is 80 km/h, and the road adhesion coefficient is set to 0.85. During the test, the steering wheel angle input of the vehicle is shown in Figure 5, the longitudinal velocity the vehicle is shown in Figure 6, the lateral acceleration at the center of mass of the vehicle is shown in Figure 7, and the tire force of the four wheels and the load transfer of the vehicle are shown in Figure 8 and Figure 9, respectively.

As shown in Figure 5, at the initial position of the test condition, the driver quickly makes a left turn of 294 degrees and then makes a right turn-back operation of 294 degrees. In this process, the longitudinal velocity of the vehicle is shown in Figure 6. The lateral acceleration change at the center of mass is shown in Figure 7, and it can be seen that the maximum lateral acceleration in the test is above 0.8g; and the tire forces curve of the four wheels is shown in Figure 8. The tire forces of the two wheels on the left side of the vehicle increases rapidly to over 8000N, while the tire force of the

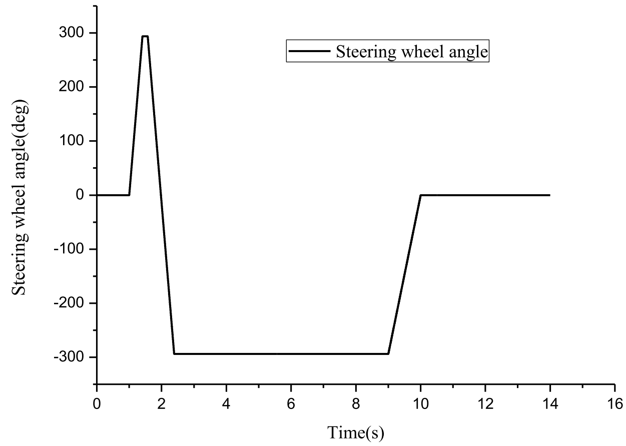

FIGURE 5. Steering wheel angle.

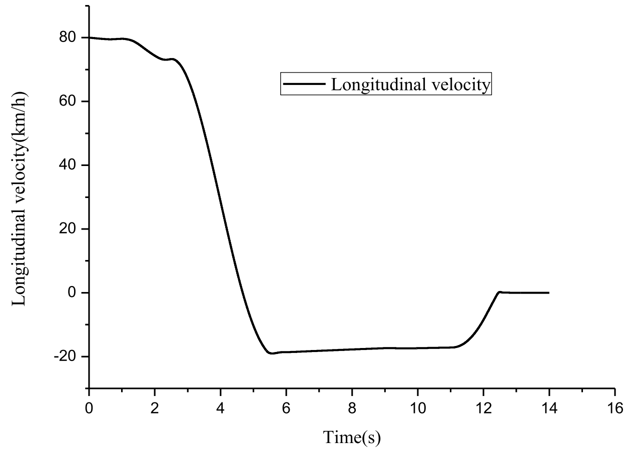

FIGURE 6. The longitudinal velocity.

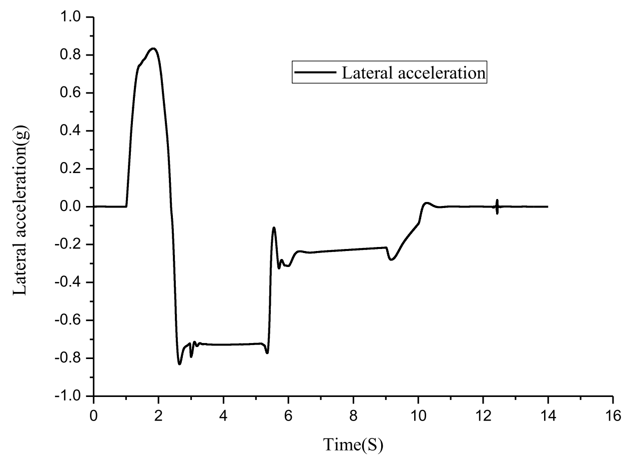

FIGURE 7. The lateral acceleration.

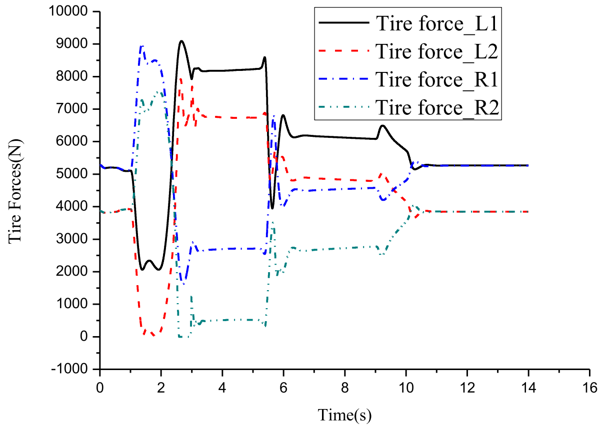

FIGURE 8. The tire forces.

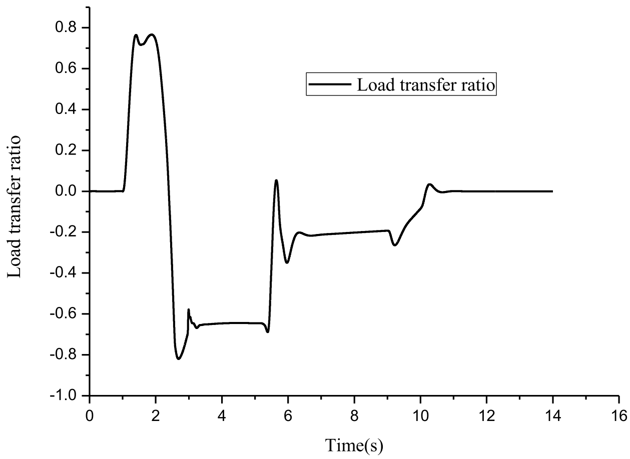

FIGURE 9. The lateral load transfer rate.

two wheels on the right side decreases to about 500N. The change of vehicle lateral load transfer rate under the whole simulation condition is shown in Figure 9. During the abrupt steering process of 2-6s, the vehicle lateral load transfer rate is close to 0.8. That is to say, during the steering process, most of the right tire force is transferred to the left tire, and the wheel is about to be lifted off in the critical state. At this time, the vehicle rollover stability is very poor.

The SVM rollover hazard empirical model is used to evaluate the rollover hazard of SUV vehicle, and the visual hypersurface is used to define the rollover hazard and safety area, which lays the foundation for the subsequent rollover warning.

Vehicle longitudinal velocity and vehicle height of mass center are selected as two random input variables of the model. The input space of the sample is defined as follows.

$$\Gamma = \left\{ \begin{array}{l} x = (V, h) \\ V \in [-20km/h, 80km/h] \\ h \in [0.672m,\ 0.688m] \end{array} \right\} \tag{27}$$

In addition, before applying the SVM model algorithm, the above two random variable vectors must be normalized

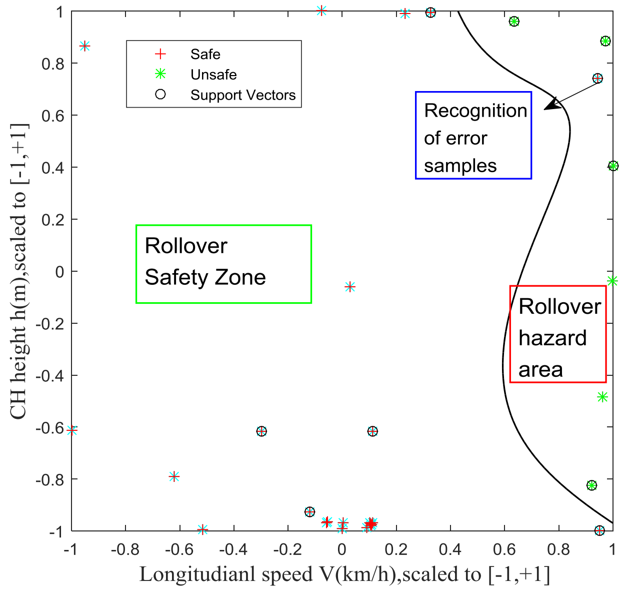

FIGURE 10. Vehicle rollover risk recognition (four-order polynomial).

so that their range of values belongs to $[-1, +1]$, so as to speed up the solution of the optimal solution. The threshold value of lateral load transfer rate $LTR_{threshold}$ in the rollover limit state function of the vehicle rollover hazard empirical model $R(x)$ is set to 0.6.

In order to verify the influence of parameters of SVM model on the prediction results of rollover hazard, this paper chooses polynomial kernel and radial basis function to compare the results of rollover hazard prediction when choosing the kernel function of SVM algorithm.

A. POLYNOMIAL KERNEL OF SVM MODEL

In this algorithm, in order to analytically describe the dangerous limit state of rollover, several multi-order polynomial kernels are defined, and different penalty factor C is selected to verify the algorithm.

(1) 4-order polynomial kernel function, penalty factor $C = 1$

(2) 5-order polynomial kernel function, penalty factor $C = 1$

Figure 10 shows that the SVM empirical model chooses a fourth-order polynomial kernel function with penalty factor $C = 1$, and there is one error sample in the recognition result. When the SVM empirical model chooses a fifth-order polynomial kernel function with penalty factor $C = 1$ in Figure 11, the recognition accuracy of the model reaches 100%. It can be seen that increasing the order of polynomial kernel function is conducive to improving the recognition accuracy of the model. At the same time, the circled samples in the empirical model mentioned above are selected as support vectors. It can be found that the polynomial kernel SVM model with less support vectors can be used to visualize rollover risk classification and recognition, and the recognition rate is satisfied.

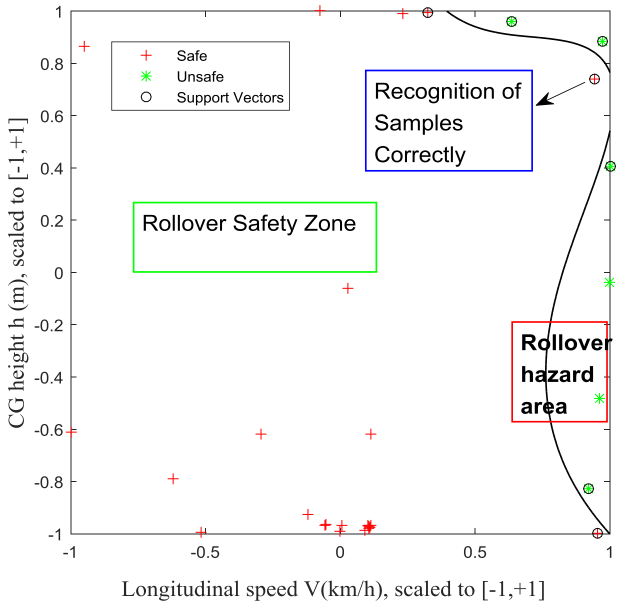

FIGURE 11. **Vehicle rollover risk recognition (five-order polynomial).**

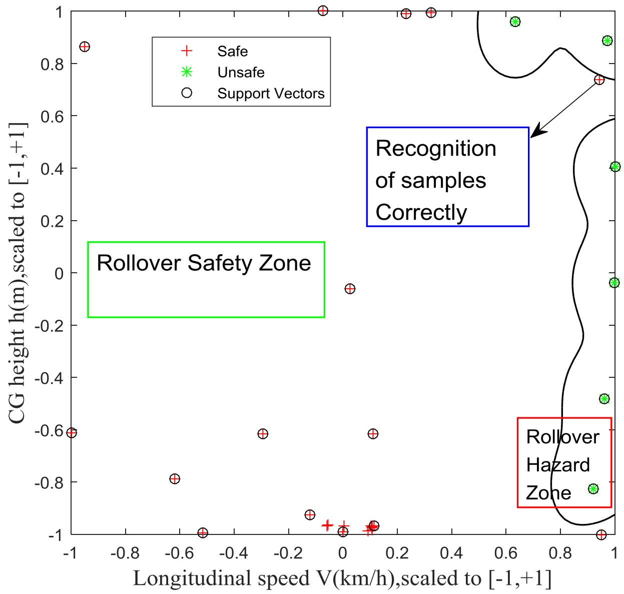

FIGURE 13. **Vehicle rollover risk identification (rbf_sigma=0.16).**

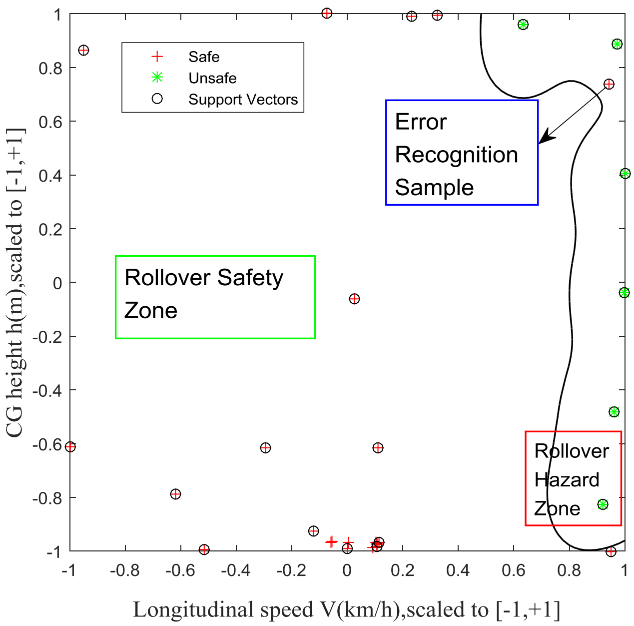

FIGURE 12. **Vehicle rollover risk identification (rbf_sigma=0.2).**

B. RADIAL BASIS FUNCTION OF SVM MODEL

In order to analytically describe the limit state of rollover, several kernels with different radial basis function coefficients are defined to verify the algorithm.

(1) Radial basis coefficient rbf_sigma=0.2

(2) Radial basis coefficient rbf_sigma=0.16

In Figure 12, when the empirical model of SVM with radial basis coefficient of 0.2 is selected, an error sample appears in the recognition result of the model, and when the radial basis coefficient of the model is set to 0.16, the recognition accuracy of the model reaches 100%. It can be seen that reducing the radial basis coefficient can effectively improve the accuracy of model recognition. At the same time, the circled samples in Figure 12and Figure 13 are the selected support vector. Compared with the polynomial-based SVM empirical model, the number of support vectors selected by the radial-based SVM empirical model is much larger than that of the polynomial-based SVM empirical model.

Vehicle rollover test is a very dangerous experiment. As the first step of the research, simulation or hardware in the loop experiment is a more practical verification method for the proposed algorithm. SVM is a small sample learning method. The advantage of SVM method is that it can achieve high accuracy of classification with small sample and nonlinearity. Other methods, such as Markov chain, Neural Networks need a large number of samples to train, which is expensive and inefficient. To verify the theoretical feasibility of SVM method in identifying the safe and unsafe zone of vehicle rollover under all conditions, simulation experiments in Carsim are carried out to collect the sample data (some data used to train the SVM empirical model and the other data for recognition to verify the proposed SVM model). The training samples include 10 rollover safety and dangerous samples (5 samples for each), through SVM algorithm training, the training results are as shown in the Fig. 14.

At the same time, an experiment with a sample containing 50 rollover safe and dangerous conditions is carried out. The experiment results are shown in the Fig.15. It can be seen that SVM method can achieve high accuracy of classification with small sample in terms of identifying the safe and unsafe zone of vehicle rollover. The recognition accuracy of the model is 100%.

The two kinds of SVM rollover hazard early warning empirical models based on two different kernel functions mentioned above can effectively identify and classify the

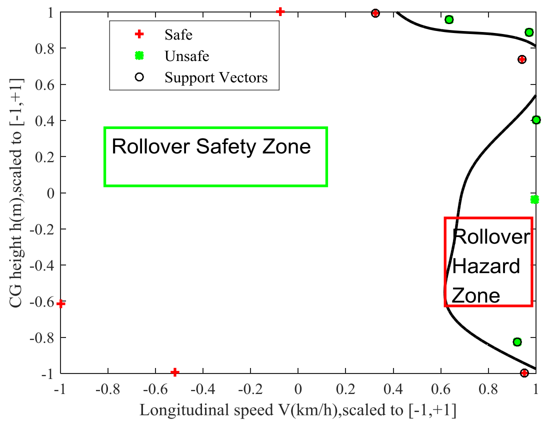

FIGURE 14. SVM training results.

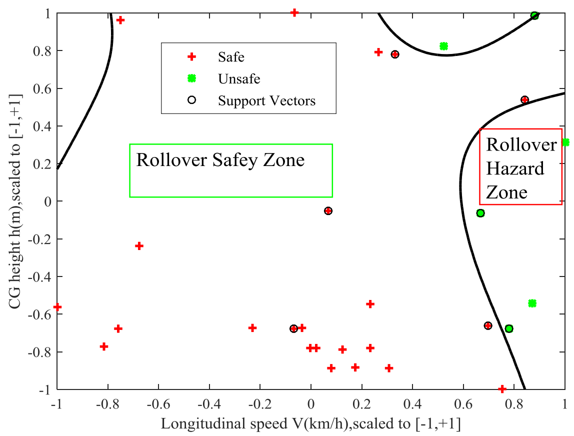

FIGURE 15. SVM experiment results.

rollover risk and safety samples of SUV vehicles, and visually define the rollover safe and hazard zones. The accuracy of model recognition is closely related to the parameter selection of the SVM empirical model. The simulation results show that, compared with the higher order polynomial kernel function and the correct radial basis function, the appropriate empirical model of SVM can ensure a high accuracy with small sample recognition. Once the parameters of the above empirical model based on SVM are trained offline, the model can be applied to the field of vehicle rollover warning and control.

V. CONCLUSION

In this paper, a vehicle rollover early warning algorithm based on the Support vector machine (SVM) model is proposed. The Support vector machine model takes into account the uncertainty of the driver-vehicle-road system and the real variability of the parameters, and provides an explicit function of the vehicle rollover safety limit and its gradient. The simulation results show that the proposed empirical model of SVM can ensure a high accuracy of rollover warning with small sample recognition.

A. PRACTICAL AND IMPLICATIONS

To prevent rollover accident, the proposed rollover risk warning algorithm can effectively identify and classify the rollover risk and safety samples of SUV vehicles, and visually define the rollover safe and hazard zones. The appropriate empirical model of SVM can ensure a high accuracy with small sample recognition.

Once the parameters of the above empirical model based on SVM are trained offline, the model can be applied to the field of vehicle rollover warning and control. In addition, the traditional vehicle rollover prediction index LTR can only be calculated by solving coupled dynamic equation, and cannot be expressed by explicit function. This paper solves this problem skillfully and it can ensure the good applicability of the proposed algorithm. At the same time, the rollover warning algorithm based on SVM empirical model can reduce the strong nonlinearity and the interference of external uncertainties.

B. FUTURE WORK

In future work, we will concentrates on some investigations: (1) Vehicle rollover test is a very dangerous experiment. As the first step of this research, simulation experiment is a more practical verification method for the proposed algorithm. In the next step, we will use it in the real vehicle test to further verify the accuracy of the proposed algorithm. In the real vehicle test, considering the availability and interference of parameters, such as measurement noise, we will select the best random variables to establish and train the SVM empirical model.

(2) In the next step, we will further study the impact of key parameters such as penalty coefficient, radial basis coefficient in the empirical model, as well as the practicability and sensitivity analysis of the algorithm.

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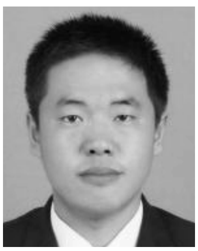

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