A Reliability Approach to Development of Rollover Prediction for Heavy Vehicles Based on SVM Empirical Model With Multiple Observed Variables

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ABSTRACT The rapid development of cooperative vehicle-infrastructure system (CVIS) improves the communication reliability between vehicles and road environment. These communications enable the accurate vehicle rollover prediction in Human-Vehicle-Road interaction. However, considering the strong non-linear characteristics of Human-Vehicle-Road interaction and the uncertainty of modeling, the traditional deterministic method cannot meet the requirement of accurate prediction of rollover hazard for heavy vehicles. In order to improve the accuracy of vehicles rollover prediction, this paper proposes a developed rollover prediction algorithm based on the multiple observed variables by combining the failure probability in reliability and the empirical model. This approach applies the probability method of uncertainty to the design of dynamic rollover prediction algorithm for heavy vehicles and establishes a classification model of heavy vehicles based on support vector machine (SVM) with multiple observed variables. The failure probability of rollover limit state of heavy vehicles is calculated by Monte Carlo Sampling (MCS), Radial-Based Importance Sampling (RBIS), and Truncated Importance Sampling (TIS), respectively. Then the Fishhook, Double Lane Change tests, and J-turn tests, simulated in TruckSim, are carried out to validate the proposed algorithm. The simulation results show that the rollover prediction algorithm based on failure probability can effectively improve the rollover prediction accuracy for heavy vehicles. Moreover, based on the communication in CVIS, the failure probability can be obtained before entering the specific road. Meanwhile, this approach can reduce the external interference of strong non-linear characteristics of Human-Vehicle-Road interaction and the uncertainty of the modeling to the system, thus improving the prediction accuracy of active safety performance of heavy vehicles significantly.

INDEX TERMS Failure probability, heavy vehicles, load transfer ratio, rollover risk prediction, SVM classification model.

I. INTRODUCTION

Heavy vehicles transport more than 80 percent of goods in the U.S., Canada, and developed countries in Europe. According to National Highway Traffic Safety Administration, Rollover accounts for 13.9% of large-truck-involved fatal crashes [1]. Due to high center of gravity, high weight, and large volume of heavy vehicles, rollover accidents tend to occur when driving at high speed, which may result in the injury to the driver and passengers and cause explosion or leakage of goods leading to environmental damages. Therefore, the research on rollover prediction and control based on the dynamics and stability of heavy vehicles has attracted worldwide attention.

The research on rollover may be categorized into active and passive rollover prevention systems. Active prevention establishes an active control strategy and device to prevent
vehicle rollover. Zhang et al. [2] proposed an active steering technique called pulsed active rear steering using the yaw and roll vehicle models. Vu et al. [3] developed a linear $H_{\infty}$ control scheme based on the yaw-roll model of a single unit heavy vehicle including active anti-roll bar systems at two axles. Li and Bei [4] developed a new algorithm applicable to the prediction of rollover risk of vehicles with large lateral velocity and high center of gravity. The algorithm calculates the ratio of rollover energy reserve to rollover threshold in real-time to obtain the rollover risk of vehicles. Moreno et al. [5] described the forces acting over the tires by Davies method, and predicted vehicle behavior more precisely under some circumstances by comparing the SSF factor in two-dimensional and three-dimensional models. Li et al. [6] used predictive control based on active braking to achieve the rollover stability control, but nonlinear characteristics and uncertainties of the automotive system are less involved. Zhu et al. [7] proposed a novel rollover prevention control system composed of rollover warning and integrated chassis control algorithm. The rollover warning based on the BP-NN technology can improve the accuracy of rollover precaution time and then the active front steering and the active yaw moment control were coordinated by model predictive control methodology. Braghin et al. [8] proposed an anti-rollover control strategy based on aerodynamic load estimation. Jalali et al. [9] designed a new roll angle estimation scheme by using conventional sensor measurements, a nonlinear observer, and a model predictive controller based on an integrated model of the vehicle roll and directional dynamics. Direct measurements of the vehicle roll-angle and roll-over index in experimental tests show the effectiveness of the proposed model predictive controller and the accuracy of the roll angle estimator. Dahmani et al. [10] used a robust controller to control roll stabilization in limit conditions.

Passive vehicle rollover protection systems, such as rollover warning systems, are commonly used to prevent rollover control. Zhang et al. [11] proposed the contour line of load transfer ratio (CL-LTR) via the roll dynamics phase plane analysis and got an accurate prediction of vehicle rollover threat based on CL-LTR. Li et al. [12] designed an improved predicted load transfer ratio IPLTR as rollover warning index. Mashadi and Mostaghimi [13] derived vehicle dynamics models after the wheels lift-off and developed the rollover threshold based on the governing equation. The best time for the prevention of the vehicle rollover is obtained by applying a correcting moment. Ataei et al. [14] proposed a new MPC-based rollover prevention system based on a new reliable RI and a more detailed vehicle model which includes the effects of the road bank and the lateral load transfer. Zhu and Zong [15] developed rollover warning and control of a heavy vehicle based on the improved TTR method. The Kalman observer is designed to estimate the vehicle roll angle in real-time to ensure the calculation accuracy of load transfer rate LTR and TTR values.

The rapid development of cooperative vehicle-infrastructure system (CVIS) improves the communication reliability between vehicles and road environment. These communications enable the accurate vehicle rollover warning in Human-Vehicle-Road interaction. Due to the strong nonlinearities of Human-Vehicle-Road interaction system and the uncertainties in Vehicle state modeling, drivers and anti-rollover control devices must control both steering and speed in time according to their dynamic response and road environment information, and then the deterioration of the driving stability of heavy vehicles will be avoided. However, because of the frequent changes of driver state, vehicle state and road information in a Human-Vehicle-Road system, accurate modeling has high uncertainty. It is difficult to achieve accurate modeling by traditional deterministic approaches. Therefore, some researchers began to pay attention to the nonlinearity and uncertainty in vehicle driving. Zhao et al. [16] proposed a displacement and force coupling control design for active front steering (AFS) system of vehicle. They designed a robust yaw rate control method considering the nonlinear characteristics of the tire force and external disturbance, and realized the road feeling control by adding a planetary gear set and an assisted motor, which can improve the cornering stability and maneuverability of vehicle. Sellami et al. [17] developed a reliability-based warning system to alert the driver to a potential rollover before entering into a bend. This warning system consists of an empirical model based on the SVM algorithm to obtain the limit state function, and assesses rollover risk through the reliability-based rollover index. This warning system considerably improved the computation performance of the reliability index. However, some prominent parameters on the rollover risk are not considered as random variables, and the warning system can’t meet requirements of more complex driving scenarios.

To solve this problem, a reliability rollover warning system adapted to complex scenarios is proposed in this paper. The method applies the probabilistic method to the dynamic rollover prediction algorithm of heavy vehicles. This approach based on CVIS can evaluate dynamic rollover risk for heavy vehicles before entering the specific road. The novelty of this research is that more parameters related to rollover risk such as random variables are considered. The explicit rollover limit state function based on SVM applied in a special complex scenario to model the uncertainties of heavy vehicles, and the failure probability of heavy vehicles are calculated by the Monte Carlo Sampling (MCS). Radial-Based Importance Sampling (RBIS), and Truncated Importance Sampling (TIS) are used to predict the rollover risk of heavy vehicles accurately.

II. RELIABILITY ANALYSIS OF A HEAVY VEHICLE SYSTEM
A. RELIABILITY DESCRIPTION OF HUMAN-VEHICLE-ROAD INTERACTIVE SYSTEM
It is an important issue to study the vehicle driving reliability in the human-vehicle-road interaction system, especially before the rollover accident occurs. This paper predicts...
the probability of vehicle rollover by observing the vehicle driving state, to enhance the fitness between human and vehicle and to improve the reliability of the human-vehicle-road interaction system. The reliability of the human-vehicle-road interaction system is not only related to the reliability of human and vehicle, but also related to the fitness of human, vehicles and roads. The reliability of human refers to the probability of those activities that human completes successfully for the reliability of the system [18]. Vehicle reliability is an important index to evaluate vehicle design and manufacture. It refers to the probability of completing the specified function of vehicle assembly or parts in the specified service time and conditions [19]. The fitness refers to the degree to which the prediction result of the vehicle driving state under the effect of road surface conforms to the actual situation.

B. VEHICLE LIMIT STATE FUNCTION

The driving state of vehicles can be divided into safety state, limit state and rollover state. In this paper, the parameters and state variables of heavy vehicles $X = (X_1, X_2, \ldots, X_n)$ establish the vehicle driving limit state function $g(X)$ to evaluate the vehicle driving state. The vehicle driving limit state is the threshold value of the vehicle driving state. If reaching the extreme value, the heavy vehicle system will be in the rollover state.

$$Z = g(X) = \begin{cases} < 0 & \text{rollover} \\ = 0 & \text{limit state} \\ > 0 & \text{safe state} \end{cases}$$

C. RELIABILITY AND FAILURE PROBABILITY

Based on the reliability theory, the rollover probability (failure probability) defines the probability that the heavy vehicle cannot complete the specified function (rollover) under the specified conditions and time. Then the failure probability $P_f$ can be obtained as the following:

$$P_f = \int_{x<0} \cdots \int f_X(x_1, x_2, \ldots, x_n) dx_1 dx_2 \cdots dx_n$$

In general, Equation (2) is numerically complex to estimate accurately. Therefore, this paper uses the Monte Carlo Sampling, Radial-Based Importance Sampling, and Truncated Importance Sampling to calculate the reliability index and rollover failure probability of a heavy vehicle.

D. MONTE CARLO

Monte Carlo Sampling is a stochastic simulation method for solving engineering problems related to random variables. The Monte Carlo Sampling is less restricted by the boundary shape of the limit state, and it has high accuracy and simple calculation especially for multi-dimensional and highly nonlinear problems. The main idea of Monte Carlo simulation is to make the mathematical expectation of experimental probability approximate to the original probability problem through a large number of experiments. As long as the number of random samples is large enough, the solution with high precision can be obtained. The method is based on large number of random variables to find the frequency of failure events, namely the failure probability.

The failure probability in reliability analysis can be obtained referring to [20]:

$$P_f = P\{g(X) < 0\} = \int_{D_f} f(X) dX$$

where, $X = \{x_1, x_2, x_3, \ldots, x_n\}^T$ is a vector with an $n$-dimensional random variable; $f(X)$ is the joint probability density function of random variables; $g(X)$ is the limit equation of state function. That is, when $g(X) < 0$, the event fails; otherwise, the event does not fail. $D_f$ defines the failure domain in accordance with $g(X)$.

The probability of rollover failure is converted into the number of rollover failures divided by the total number of tests. Monte Carlo method is used to calculate the system failure probability as follows [21]:

$$\hat{P}_f = \frac{1}{N} \sum_{i=1}^{N} I[\hat{g}(\hat{x}_i)]$$

$$I[\hat{g}(\hat{x}_i)] = \begin{cases} 1 & g(\hat{x}_i) < 0 \\ 0 & g(\hat{x}_i) > 0 \end{cases}$$

E. RADIAL-BASED IMPORTANCE SAMPLING

Monte Carlo requires large number of samples to ensure sufficient accuracy, which is not possible in many cases. Radial-Based Importance Sampling improves the computational efficiency by the truncated joint probability density function. The main principle of this importance sampling is that: in the standard normal space, the importance sampling only covers areas outside the $\beta$ sphere, reducing the sampling of the safe areas. The $\beta$ sphere is a hypersphere with the origin as the center and the distance from the design point to the origin as the radius. Hasofer and Lind [22] proposed that the reliability index is the shortest distance from the origin of the standard normal space to the limit state surface. And the design point on the limit state surface can be determined at the same time.

The random variables $(x_1, x_2, \ldots, x_n)$ establish a structure limit state equation $Z = g(x_1, x_2, \ldots, x_n) = 0$. According to the geometric meaning of the reliability index $\beta$, this index and the design point $x^* = (x^*_1, x^*_2, \ldots, x^*_n)$ will be obtained following the optimization model:

$$\min \beta^2 = \sum_{i=1}^{n} \left[ (x^*_i - \mu_i) / \sigma_i \right]^2$$

subject to $Z = g(x_1, x_2, \ldots, x_n) = 0$.

The $\beta$ sphere, based on the design point, divides the variable space into two parts. Then the failure probability can be written as:

$$P_f = P\{g(x) < 0\} = P\{g(x) < 0 \| \|x\| \geq \beta_0\} P\{\|x\| \geq \beta_0\}$$

$$+ P\{g(x) < 0 \| \|x\| < \beta_0\} P\{\|x\| < \beta_0\}$$

$$= P\{g(x) < 0 \| \|x\| \geq \beta_0\} P\{\|x\| \geq \beta_0\}$$
The Monte Carlo sampling can estimate the conditional probability \( P\{g(x) < 0 | \|x\| \geq \beta_0\} \): 
\[
P_f = \frac{N_f}{N} \cdot P\{\|X\| > \beta_0\} \tag{8}
\]
where \( N \) is the total number of samples (outside the sphere) 
\( N_f \) is the number of samples when \( g \) is less than zero.

To calculate the probability of the region outside the sphere \( P\{\|x\| \geq \beta_0\} \), the independent normal random variables map the one-dimension variable conforming to standard normal space. According to the standard normal distribution table, \( \Phi(3) = 0.9974 \), the value of most variables vary in a range of \([-3, 3]\). The area of the unsampled region is inside \( \beta \) sphere.

According to the geometric probability, the probability \( P_s \) of the unsampled region is the ratio of the volume between the hypersphere and hypercube in normalized space:
\[
P_s = \frac{V_{\text{hypersphere}}}{V_{\text{hypercube}}} = \frac{\pi^{\alpha/2}}{\Gamma(\alpha/2 + 1)} \frac{\beta^{\alpha}}{d^n} \tag{9}
\]
where, \( r \) is the radius of the hypersphere 
\( d \) is the length of the hypercube 
\( n \) is the dimension of the hypercube 
\( \Gamma \) is a gamma function, defined as
\[
\Gamma(t) = \int_{0}^{+\infty} x^{t-1} e^{-x} dx, \quad t > 0 \tag{10}
\]
where, \( t \) is a natural number, \( \Gamma(t) = (t-1)! \)

Then the probability \((1-P_s)\) of sampling area follows the density function of the standard normal distribution:
\[
P(\|x\| \geq \beta_0) = 2 \cdot (1 - \Phi(6P_s/2)) \tag{11}
\]
The final failure probability becomes:
\[
P_f = \frac{N_f}{N} \cdot 2 \cdot (1 - \Phi(3P_s)) \tag{12}
\]
The steps of Radial-Based Importance Sampling include:

1. Use the optimization toolbox to find the design point and calculate the radius of the \( \beta \) sphere in the standard normal space;
2. Generate sample points that obey the joint probability density function;
3. Record the sample points whose distance to the origin is greater than the design point in the standard normal space.
4. Calculate the function value of the recorded points and the failure probability of the sampling area by Monte Carlo;
5. Calculate the probability of sampling area and calculate the final failure probability.

\section*{F. TRUNCATED IMPORTANCE SAMPLING}

The Truncated Importance Sampling [23] is similar to Radial-Based Importance Sampling. This sampling method establishes a Truncated Importance Sampling function outside \( \beta \) sphere. This method can reduce the sampling in the safety area and improve the sampling efficiency.

In standard normal space, the square of the distance from the design point to the origin follows \( \chi^2 \) distribution of \( n \) degrees of freedom. Then the failure probability is
\[
P_f = P\{g(x) < 0 | \|x\| \geq \beta_0\} (1 - \chi^2(\beta_0^2)) \tag{13}
\]
To calculate the conditional probability \( P\{g(x) < 0 | \|x\| \geq \beta_0\} \) in the above equation, the truncated joint probability density function is used in Truncated Importance Sampling. when \( \|x\| \geq \beta_0 \), the truncated probability density function of the random variables \( f_i(x) \) follows:
\[
f_i(x) = \begin{cases} 
0 & \|x\| < \beta_0 \\
f_{\|x\| \geq \beta_0}(x) & \|x\| \geq \beta_0 
\end{cases} \tag{14}
\]
where \( f_{\|x\| \geq \beta_0}(x) \) is the joint probability density distribution function of \( x \).

Therefore, the conditional probability of failure probability is
\[
P\{g(x) < 0 | \|x\| \geq \beta_0\} = \int_{\|x\| \geq \beta_0} f_{\|x\| \geq \beta_0}(x) dx = \int_{\|x\| \geq \beta_0} \prod_{i=1}^{n} f_i(x) dx \tag{16}
\]
The important sampling computes the integral of the equation. The original importance sampling function \( h_{\|x\|}(x) \) is also truncated by the \( \beta \) sphere, and the truncated sampling density function \( h_{t}(x) \) is defined as
\[
h_t(x) = \begin{cases} 
0 & \|x\| < \beta_0 \\
\frac{1}{P_{ht}} h_{\|x\|}(x) & \|x\| \geq \beta_0 
\end{cases} \tag{17}
\]
\[
P_{ht} = \int_{\|x\| \geq \beta_0} h_{\|x\|}(x) dx \tag{18}
\]
where, \( P_{ht} \) is the probability of the original importance sampling function \( h_{\|x\|}(x) \) outside the \( \beta \) sphere.

The conditional probability can be rewritten as
\[
P\{g(x) < 0 | \|x\| \geq \beta_0\} = \int_{\|x\| \geq \beta_0} \frac{I(x)f_t(x)}{h_t(x)} h_t(x) dx = E_{ht}(I(x)f_t(x) h_t(x)) \tag{19}
\]
Finally, the failure probability becomes
\[
P_f = E_{ht}(I(x)f_t(x) h_t(x)(1 - \chi^2(\beta_0^2))) \tag{20}
\]
where \( E_{ht} \) is the mathematical expectation of the truncated sampling density function \( h_t(x) \).

The steps of Truncated Importance Sampling include:

1. Use the optimization toolbox to find the design points and calculate the radius of the \( \beta \) sphere in the standard normal space;
(2) Generate samples with probability density distribution of \( h_i(x) \).

Firstly, generate the standard normal random number \( r_i \), then compute \( x_{ji} = x_i^* + \sigma_i r_i \), where \( x_{ji} \) is the \( i \)th vector in the \( j \)th sample \( x_j \).

(3) Use the screening method to obtain samples \( x_k \) (1, 2, ..., \( N \)) with truncated density distribution of \( h_i(x) \). That is, the sample point whose distance to the origin in the standard normal space is greater than the radius of the \( \beta \) sphere.

(4) Use the obtained sample points to estimate their failure probability referring to (20).

G. RELIABILITY CALCULATION OF VEHICLE ROLLOVER

The main rollover indicators include lateral acceleration, lateral inclination, lateral load transfer rate (LTR), and time to rollover (TTR). The lateral load transfer rate has a fixed rollover threshold and is suitable for all types of vehicles.

Load transfer ratio indicates the vertical load transfer of the tires from one side to another side, and it can be calculated as following [24]:

\[
LTR = \frac{\sum_{i=1}^{n} (FL_i - FR_i)}{\sum_{i=1}^{n} (FL_i + FR_i)}
\]  

(21)

where, \( FL_i \) and \( FR_i \) are the vertical loads on the wheels of the vehicle; \( i \) is the position of axles; \( n \) is the total number of axles.

The value of \( LTR \) varies between \([-1, 1] \). Once the absolute value of \( LTR \) is greater than the stability threshold, the vehicle will roll over. Therefore, the rollover probability (i.e., the failure probability) of heavy vehicles can be rewritten as:

\[
P_f = P\{g(X) = LTR_{th} - |LTR| < 0\} = \int f(X)dx
\]

(22)

where, \( LTR_{th} \) is the stability threshold of the vertical loads on the wheels of the vehicle.

The diagram of Fig. 1 summarizes the calculation process of the heavy vehicle rollover failure probability.

The failure probability of heavy vehicles entering unsafe domains (rollover) becomes:

\[
P_f = P\{g(X) < 0\} = \int_{D_f} f_X(x)dx = \int_{-\infty}^{0} f_Y(y)dy
\]

(23)

where, \( D_f = \{x \in R^n/ g(x) < 0\} \) is an unsafe domain; \( f_X(x) \) is the joint probability density function of random variable \( X \); \( f_Y(y) \) is the joint probability density function of random variable \( Y \), and \( Y = g(X) \).

The random variable \( X \) and its mapping \( Y \) are nonlinear random variables, and it is hard to get the exact values of the two integrals in (23) by traditional numerical calculation methods. Although the Monte Carlo Sampling, Radial-Based Importance Sampling, and Truncated Importance Sampling can accurately obtain the estimated value in (23), they have low computational efficiency and poor real-time performance under low probability values [25].

In order to improve the computational efficiency of the algorithm, the SVM empirical model is established to obtain the explicit function of the limit state. The support vector reduces the complexity of the original problem and ensures the real-time performance of the algorithm.

III. SUPPORT VECTOR MACHINE EMPIRICAL MODEL

A. SVM ALGORITHM

The Support Vector Machine (SVM) is a machine learning method proposed by Vapnik based on the minimization principle of structural risk. It has many unique advantages in solving the classification problems of small samples, nonlinear, and high dimensional data sets [26].

The classification idea of SVM refers to searching for the optimal classification surface under linear separable condition. As Fig. 2 shows, squares and circles are two kinds of sample points. \( H \) is the optimal classification line of two kinds of samples. \( H_1 \) is the parallel closest to \( H \) and goes through the square. \( H_2 \) is the parallel closest to \( H \) and goes through the circles. The margin is the vertical distance between \( H_1 \) and \( H_2 \), support vectors are the point set nearest to the optimal classification line in training set (i.e., the points on the \( H_1 \) and \( H_2 \)).

The two-class support vector machine algorithm is as the following: the training data set are \((x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n), x \in R^n, y \in \{+1, -1\}\). The linear discriminant function...
as:

$$g(x) = (w^T x) + b$$

(24)

The discriminant function is normalized, so that all the samples of both classes satisfy $|g(x)| \geq 1$. The main idea of SVM algorithm is to maximize the soft interval, which is the maximum interval between support vector and classification surface. Hence the margin classification interval is defined as:

$$\text{margin} = \frac{2}{\|w\|}$$

(25)

The optimal classification interval problem converts to a dual problem to obtain the maximum of margin. [25].

$$\begin{align*}
\min \phi(w) &= \frac{1}{2} \|w\|^2 \\
y_i[(w^T x) + b] - 1 &\geq 0, \quad i = 1, 2, \ldots, n
\end{align*}$$

(26)

Then the dual problem is solved by using Lagrange optimization method:

$$L(a) = \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i,j=1}^{n} a_ia_jy_iy_j(x_i,x_j)$$

(27)

$$\sum_{i=1}^{n} y_ia_i = 0, \quad a_i \geq 0, \quad i = 1, 2, \ldots, n$$

(28)

According to karush-kuhn-tucker condition (KKT), only a few of the solutions $a_i$ in (27) are non-zero, and the non-zero solutions $a_i$ are support vectors [27]. Training the support vectors obtains the optimal solution of $L$ as the following:

$$w^* = \sum_{i=1}^{n} a_i^* y_ix_i$$

(29)

$$b^* = y_i - \sum_{j=1}^{n} a_j^* y_j(x_j \cdot y_j), \quad \forall i \in \{i | a_i^* > 0\}$$

(30)

The optimal classification function is obtained by the explicit function of the limit state function [28]:

$$g(x) = \text{sgn} \{ (w^* \cdot x) + b^* \}$$

$$= \text{sgn} \{ \sum a_i y_i(x_i \cdot x) + b^* \}$$

(31)

where $\text{sgn}()$ is a symbolic function. Since $a_i$ corresponding to the non-support vector is zero, the summation in the above equation is only performed on the support vector.

**B. EXPLICIT FUNCTION OF ROLLOVER LIMIT STATE FUNCTION**

For nonlinear problems, the SVM transforms the nonlinear problem of a low dimensional space into a linear problem of a high dimensional space by establishing a kernel function. At present, the main kernel functions include linear kernel function, polynomial kernel function, radial basis kernel function and Sigmoid kernel function. The radial basis kernel function is widely used for its strong learning ability. The radial basis kernel function is defined as:

$$K(x_i, x_j) = \exp \left( -\frac{|x_i - x_j|^2}{2\sigma^2} \right) = \exp \left( -g \cdot |x_i - x_j|^2 \right)$$

(32)

The optimal classification function of the kernel function (the explicit function of the limit state function) corresponding to (31) can be expressed as:

$$g(x) = \text{sgn} \{ \sum a_i y_iK(x_i, x) + b^* \}$$

(33)

For the case of linear inseparability, some training samples cannot satisfy $|g(X)| \geq 1$, therefore, penalty factor $C$ is set to reduce the sample misclassification rate. The value of $C$ will affect the classification ability of SVM. Fewer values of $C$ decline the learning ability of classification algorithm and the classification algorithm will be in the state of under-learning. High values of $C$ tend to be over-learning [29].

**IV. ROLLOVER RISK PREDICTION ALGORITHM BASED ON SVM EMPIRICAL MODEL**

The limit state function $g(x)$ for heavy vehicles based on SVM empirical model divides the driving state of vehicles into safety state and rollover state, and the explicit formula of this limit state function will be used for the probability of rollover failure. Then, the rollover failure probability of heavy vehicles is obtained based on Monte Carlo Sampling (MCS), Radial-Based Importance Sampling, and Truncated Importance Sampling theory. Finally, according to the calculated results, the rollover risk of heavy vehicles is predicted in real time. Fig. 3 summarizes the algorithm flow.

The input variables of the SVM empirical model includes deterministic and random variables (see Fig. 3). The deterministic variables determine vehicle performance parameters, such as vehicle mass parameters and inertia parameters (see Table 1). The random variables used in the study contain the height of the center of gravity, lateral acceleration, yaw
FIGURE 3. Diagram of rollover risk prediction algorithm based on the reliability index and SVM empirical model.

TABLE 1. Deterministic variables and their values.

| Deterministic Variable          | Value       |
|---------------------------------|-------------|
| Vehicle mass                    | 6789 kg     |
| Sprung mass                     | 4457 kg     |
| Roll moment of inertia          | 2310.5 km m²|
| Pitch moment of inertia         | 35443.8 km m²|
| Yaw moment of inertia           | 34693.7 km m²|

FIGURE 4. Flow chart of simulation verification for rollover risk prediction algorithm of heavy vehicles.

angular velocity, and roll angle, which significantly influence the rollover state. During vehicle driving, the value of the random variable can be obtained based on the observed data. Then the rollover state is calculated based on the SVM empirical model. Finally, the rollover probability of the vehicle is obtained by the reliability method (Monte Carlo Sampling, Radial-Based Importance Sampling, and Truncated Importance Sampling). As the input data with different dimensions ranges widely, each input variable of the empirical model needs to be normalized before calculation, so that it is scaled to the range $[-1, +1]$. The Human-Vehicle-Road model is built by TruckSim software based on the above vehicle parameters [30]. The classification based on SVM empirical model can accurately separate domains of the safe-driving from domains of rollover. Moreover, the limit state function is obtained to calculate the rollover failure probability of heavy vehicle.

V. APPLICATION OF ROLLOVER RISK EVALUATION

It is noted that when the vehicle is driving, the road environment information of the vehicle can be obtained in advance, based on the vehicle-road collaborative system. This information can be used to obtain the rollover probability of the road section before the vehicle enters this road. In order to apply this reliability approach, the data of these cases are obtained from TruckSim.

A. SIMULATED DATA PROCESSING

The rollover risk prediction algorithm of a heavy vehicle can be verified through the steps summarized in Fig. 4:

To obtain an accurate SVM empirical model, TruckSim simulates fishhook tests and double lane change tests for 5 times respectively to obtain the training data. The test data contain the observation data obtained from the simulation of twice fishhook tests and twice double lane change tests respectively. Each simulation can obtain about 700 sets of observation data. All the observation data are used to train and test the accuracy of SVM empirical model. Besides, to establish the SVM model more accurately, the samples near the rollover limit state are increased by copying the data with high load transfer ratio in the training set. Moreover, the main parameters that affect the SVM performance are gamma (g) and penalty factor C. Gamma affects the range of gauss for each support vector. When the gamma is large enough, SVM based on RBF kernel function can correctly classify all training samples, which tends to be over-learning.
When gamma is small enough, all samples are classified into the same class. The punishment parameter C controls the punishment degree of the misclassified samples. The higher C causes the higher punishment degree of the misclassified samples. To avoid the problems of over-learning and under-learning in the SVM algorithm, this paper selects 10 sets of observation data as its training set, and optimizes the penalty parameter C and kernel function g by grid searching. The accuracy of the optimization results was 99.933% (see Fig. 5 - Fig. 6). Then, the test set verified the SVM classified model. The classification accuracy of SVM model was 95.663%.

In reliability calculation, the distribution of random variables directly affects the calculation results of reliability. The random variable following the normal distribution shows good performance in the calculation of rollover failure reliability, during vehicle driving [31]. To simulate the influence of uncertain factors when vehicle is at work, the random sampling follows normal distribution based on the observed data. The observed data are used as the sampling center to simulate the rollover failure of the corresponding observed data points. The variance of the random sampling represents the degree of dispersion of the data. To achieve accurate calculation of vehicle rollover failure, the probability of vehicle rollover failure under different variances is calculated (see Fig. 7 - Fig. 9).

When the variance was small, it failed to reflect the change of vehicle rollover failure risk. When the variance was large, it tended to cause false alarm. Therefore, 0.2 times the observed value is chosen as the variance of the normal distribution.

According to the above research, the vehicle rollover failure probability can be summarized as the following steps:
Firstly, the observation data are obtained from TruckSim to simulate the actual measured data. Then, to simulate the impact of uncertain factors during vehicle driving, the simulation sample points based on the observation data are generated by the normal distribution random number generator (normrnd) in MATLAB. Meanwhile, the sampling method changes with the reliability calculation method (see Table 2). Moreover, the probability of rollover failure is calculated based on the reliability method (Monte Carlo Sampling, Radial-Based Importance Sampling, and Truncated Importance Sampling). Finally, the rollover risk of heavy vehicles based on SVM is used to alert drivers.

The center of mass of a heavy vehicle becomes higher when it is driving with goods. Vehicles tend to rollover when people change lanes suddenly or turn the steering wheel rapidly. This paper carried out simulation verification for the condition of vehicle rollover. These conditions that the vehicle is prone to rollover mainly include the fishhook condition, double lane change condition, and J-turn condition.

**B. FISHHOOK**

Firstly, TruckSim software is used to establish the dynamic model of heavy vehicles and to simulate a fishhook maneuver. The steering wheel angle was set according to Fig. 10, the road adhesion coefficient was 0.85, the initial speed was 65 km/h, and driver follows aggressive driving according to Fig. 11, then observation data (the height of the center of gravity, lateral acceleration, yaw rate, and roll angle) are obtained from TruckSim (see Fig. 12 - Fig. 15) during a fishhook maneuver.

Besides, the lateral load transfer ratio of heavy vehicles was calculated by the vertical load of the wheels on both sides from TruckSim software (see Fig. 16). Once the observed data are available, the rollover failure probability based on reliability method begin to calculate. Finally, the failure probability of heavy vehicle rollover was calculated in Fig. 17.

**C. DOUBLE LANE CHANGE**

The double lane change was simulated according to Fig. 18. The road adhesion coefficient was 0.80, and the initial speed was 80 km/h. The steps of data processing are the same as those of the fishhook test, and they will not be described here. Fig. 19 - Fig. 22 show the vehicle state in the double lane change condition. Fig. 23 shows the lateral load transfer...
FIGURE 12. Lateral acceleration diagram during a fishhook maneuver.

FIGURE 13. Yaw rate diagram during a fishhook maneuver.

FIGURE 14. Roll angle diagram during a fishhook maneuver.

FIGURE 15. C.G. height diagram during a fishhook maneuver.

FIGURE 16. Load transfer ratio diagram for the fishhook maneuver.

FIGURE 17. Failure probability diagram for the fishhook maneuver.

ratio in double lane change condition. The curves of failure probability are revealed in Fig. 24.

**D. J-TURN MANEUVER**

The J-turn maneuver was simulated according to Fig. 25. The road adhesion coefficient was 0.80, and the initial speed was 65 km/h. The steps of data processing are the same as
Those of the fishhook test, and they will not be described here. Fig. 26 - Fig. 29 show the vehicle state in the J-turn condition. Fig. 30 shows the lateral load transfer ratio in the J-turn condition. The curves of failure probability are revealed in Fig. 31.
Fig. 16, Fig. 17, Fig. 23, Fig. 24, Fig. 30, and Fig. 31 presents the same trend between the load transfer ratio and failure probability during the vehicle driving. This algorithm can identify vehicle rollover status effectively. According to Sel-lami and Imine, Monte Carlo simulations are also applied to validate the estimation of the probability of rollover fail-
The maximum error of Radial-Based Importance Sampling is 0.181. The difference between the Truncated Importance Sampling and Monte Carlo Sampling is less than 0.093. A good concordance is obtained between the three methods as illustrated in Table 3. As the three sampling schemes are different in sampling, the differences of the failure probability are inevitable. However, the gap among the three methods is less than 0.181, which is acceptable. In practical application, because the lateral load transfer rate of vehicle is hard to obtain accurately, it is liable to be interfered, hence the proposed vehicle rollover probability algorithm is more suitable for the prediction of the rollover risk.

**VI. CONCLUSION**

This work aimed to propose a rollover risk prediction algorithm based on the SVM empirical model of the failure probability for heavy vehicles. The SVM empirical model is established by four parameters related to rollover risk, and is combined with the reliability method, including Monte Carlo Sampling, Radial-Based Importance Sampling, and Truncated Importance Sampling, to calculate the vehicle rollover failure probability. Then, the accurate prediction of heavy vehicle rollover risk is achieved, during vehicle driving in complex scenario.

The rollover failure probability of heavy vehicles is calculated through the SVM empirical model to achieve the prediction of the rollover risk of vehicles. This empirical method can replace the lateral load transfer ratio which is difficult to obtain accurately. The efficiency of the algorithm is verified by the fishhook, double lane change, and J-turn tests in TruckSim. The simulation results show that a good concordance is obtained from the three reliability methods and the algorithm based on failure probability is accurate. In the future, more training will be carried out before safe application in the real vehicle.

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