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Research of the vehicle rollover warning based on HMM and BP neural network

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Abstract. A rollover warning methodology for the Sport Utility Vehicle (SUV) based on Multidimensional Gaussian Hidden Markov Model (MGHMM) and BP Artificial Neural Network (ANN) is proposed. The roll angle and lateral acceleration are used as the observed sequence of HMM and the motion status are taken as the state sequence of HMM. The Baum-Welch algorithm is adopted to train the HMM and the Markov prediction algorithm is applied to forecast the motion status of the vehicle in the near future (3 s). The unnecessary ANN training is reduced while the training efficiency and prediction accuracy are improved by using the predicted vehicle movement status as a guideline to make the ANN learn purposefully. The simulation result show that the established rollover warning method not only can predict the vehicle movement status, but also can forecast specific movement parameters, which can be used by the driver to judge the rollover quantitatively as well as providing data for the anti-rollover electronic control system with less parameters and high efficiency.

Key words. Hidden markov model, rollover warning, artificial neural networks, vehicle motion status, motion parameters.

1. Introduction

Recently, vehicle rollover accident happen frequently and bring huge loss of life and property to the passenger. Compared with other vehicles, Sport Utility Vehicle has higher center of mass and the stability of vehicle rollover is low relatively, so it has become an important problem in road safety as its high rollover accident rate. It makes sense to improve the predictability of vehicle rollover accident and provide reliable early warning information for the driver by the way of installing rollover

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warning device on the vehicle in order to reduce rollover accidents.

The hidden Markov model (HMM) is suitable for dynamic time series modelling and has strong ability of sequential pattern classification, especially suitable for non-stationary and signal analysis with poor repeatability reproducibility [1]. The Hidden Markov model has been paid more and more attention in the prediction of system state and has been widely used in industrial production and automobile industry. Gautam B. Singh and Haiping Song [2] presented a collision detection system forecasting vehicle collision in the near future (6 seconds) via current vehicle state. It has the characteristics with detecting accurately and quickly, furthermore, its implementation is simple and it uses only two sensors. Gadepally [3] developed an unmanned vehicle running status estimation and prediction system, in which a HMM is used to estimate vehicle status and a hierarchical hidden Markov model (HHMM) is adopted to predict driver behavior. Maghsood [4] designed a vehicle running status (straight driving, or turning) identification system based on HMM. The system uses the lateral acceleration information of heavy trucks to identify the vehicle running status (left turn, right turn, straight driving) and this method can be extended to the identification of braking, acceleration and other driving conditions. P Raksineharoensak [5] put forward a kind of direct yaw moment control algorithm based on the driver's steering intention identification, which apply HMM to realize driver steering intention identification. The current driver steering intention is identified according to digitized data of driver operating and the trained HMM. Finally, based on the identification results, a direct yaw moment control algorithm is chosen. Berndt [6] constructed driving behavior recognition feature vector by acquiring relevant vehicle sensor information. The probability of a certain driving behavior is predicted using hidden Markov model. On this basis, lane departure and the following driving behavior can be identified via correcting the probability combining driver's driving action data. Lin [7] proposed a vehicle status identification system based on HMM and digital image, which calculates and predicts the longitudinal speed of a moving vehicle in real-time using the recording data of vehicle image. Yerim Choi [8] applied hidden Markov models (HMMs) as hypovigilance detection models for unmanned combat aerial vehicles (UCAVs) so as to reduce the high accident rate of UCAVs. To evaluate the efficacy and effectiveness of the proposed models, two experiments were conducted on the real-world data, and satisfactory results were yielded. In order to realize the auxiliary driving and achieve the goal of improving the active safety, an integrated model based on the artificial neural network and the hidden Markov chain was proposed to identify and predict the driving intentions and behaviors [9]. Experimental results proved that the model can accurately identify the current driving intention and accurately predict the next driving behavior under a given speed.

This paper designs a simple rollover warning system based on the hidden Markov model and BP Artificial Neural Network aiming at solving the problem of SUV non tripped rollover, which only needs the information of roll angle and lateral acceleration. Moreover, Multidimensional Gaussian Hidden Markov Model is set up. After the model training and vehicle motion status identification are conducted based on the data collected in multiple working conditions, the Markov prediction algorithm is used to predict vehicle rollover state. The unnecessary ANN training is reduced while the training efficiency and prediction accuracy are improved by using the predicted vehicle movement status as a guideline to make the ANN learn purposefully, the model which combines the HMM with the Artificial Neural Network (ANN) can predict the vehicle motion parameters which can be used by the driver to judge the rollover intuitively as well as used by the electronic control system to control the rollover.

2. The experimental data acquisition and preprocessing

2.1. Experimental data acquisition process based on Carsim

This paper adopts a SUV from D-class of Carsim software to conduct the simulation experiment, the specific parameters of the D-class SUV model are shown in Table 1. In this paper, the simulation are implemented in the four typical conditions, step turning, double lane change, ramp steering and fish-hook manoeevre. The test speed is 100 km/h.

Table 1. Main parameters of D-class SUV vehicle model

Symbol	Description	Value
m_1	whole vehicle quality	1530 kg
m_2	sprung mass	1370 kg
J_z	turning moment of inertial about vertical axis	$4607.4\,\mathrm{kg \cdot m^2}$
J_x	roll moment of inertial about roll axis	$708\,\mathrm{kg \cdot m^2}$
d	wheel base	2.8 m
l_v	distance from C. G. to front axle	1.1 m
l_h	distance from C. G. to rear axle	1.7 m
h	height of C.G. from a roll center	0.5 m
i	Steering system gear ratio	20

2.2. Experimental data preprocessing

The motion status parameters (lateral acceleration, roll angle) of vehicle in four conditions which constitute the HMM database are collected by using Carsim software. The collected data needs to be preprocessed according to the proceeding shown in Figure 1 before they are used to train the HMM.

Firstly, the data collected by simulation are divided into four categories according to the vehicle motion status: driving straight ahead, steering normally, steering quickly and rollover. At the same time, the classified data are divided into several segments. In this paper, the lateral acceleration and roll angle in each class are divided into 20 sets of data, so that the cluster analysis and model training can be carried out well. The data need to be standardized and normalized as the data which obtained after segmentation is very messy. Finally, the K-means algorithm is used to cluster the data and the bound value of the motion status are set.

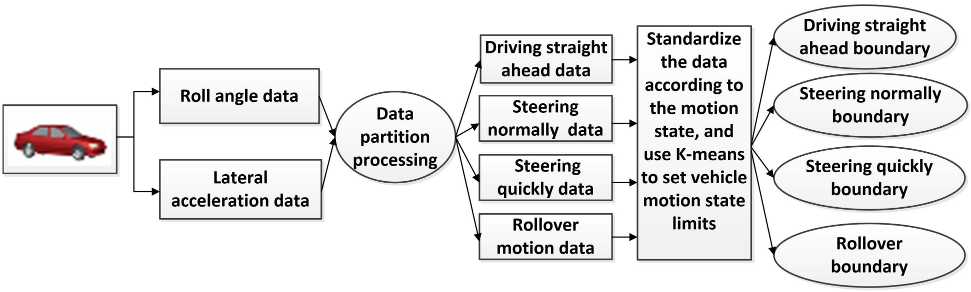

Fig. 1. Preprocessing process of acquisition data

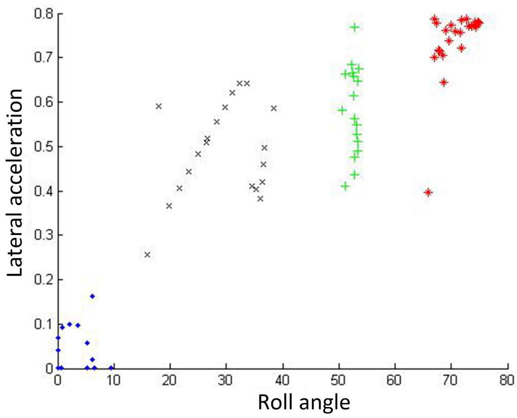

Fig. 2. The limits of vehicle motion status

The data standardization includes central processing and dimensionless processing [10]. The central processing refers to the translation transformation, the way commonly used to eliminate the dimension is compression processing to variables, which aims to change the variance of each variable to 1. In practical applications, data are often centralized and compressed at the same time, i.e., data standardization process. The "0 means standardization" method is applied in this paper.

$$x_{ij}^{*} = \frac{x_{ij} - \bar{x}_j}{s_j}\,. \tag{1}$$

Where, $\bar{x}_j$ is mean of all sample data, s_j is standard deviation of all sample data.

The mean of x_{ij} is 0, and its variance is 1 after standardization, and the covariance of any two variables is exactly equal to their correlation coefficient. Thus, the influence of dimension and order of magnitude are eliminated by such processing, which benefits greatly the following training modeling.

The raw data will be enlarged and shrinked according to certain rules, which will fall to a relatively small interval. The interval is [0, 1] in this paper.

The boundary value for vehicle motion status is determined based on K-means clustering algorithm. After the K-means algorithm is programmed through MATLAB, the clustering calculation are performed on the experimental data. Figure 2 is the clustering results of the experimental data. The data are clustered into four classes, where the black dots in the bottom left corner represent the driving straight ahead status, the $\times$ dots in the second part represent the steering normally status, the $+$ dots in the third part represent the steering quickly status and the black dots at the far right in the fourth part represent the rollover status. The boundaries of four motion status are set by clustering, so that the data can be classified based on boundary values of motion status, when the HMM model is used to identify the data segment. The clustering calculation lays the foundation for the identification results of the model.

3. Training and prediction of vehicle rollover warning model based on HMM

3.1. Multi-dimensional Gaussian HMM for vehicle motion status

The observation vector sequence of the model can be represented by $O = \{O_1, O_2, \cdots, O_{\mathrm{K}}\}$, where O_{K} is the k-th observation vector sequence, $O_{\mathrm{K}} = \{O_1, O_2, \cdots, O_t\}^T$, O_t is the t-th observation sequence, the hidden state sequence is $Q = \{q_1, q_2, \cdots, q_n\}$, thus MGHMM can be described as

$$\lambda = (\pi, A, C, \mu, U)\,,$$

Where, π is initial state distribution, A is state transition probability matrix, C is mixed weight matrix, μ is mean matrix and U is covariance matrix.

The observable sequence of MGHMM model is generated by Gauss probability density function, and the observation sequence is generated by the following mixed Gauss probability density function,

$$b_{t,n}(o) = \sum_{m=1}^{M} c_{nm} b_{t,nm} =$$
$$= \sum_{m=1}^{M} c_{nm} \times \frac{1}{\sqrt{2\pi U_{nm}}} \exp[-\frac{1}{2U_{nm}}(O_t - \mu_{nm})^T (O_t - \mu_{nm})]\,, \tag{2}$$

where, $b_{t,nm}$ is a single Gauss probability density function of the m-th component in the n-th state, U_{nm} is the m-th covariance matrix of the Gauss density in the state n, μ_{nm} is the m-th mean vector of the Gauss density in the state n, c_{nm} is the m-th mixed weight of the Gauss density in the state n.

Four Multi-dimensional Gauss hidden Markov models are established respectively, corresponding to the four motion status of vehicle: driving straight ahead, steering normally, steering quickly and rollover.

The GHMM models are trained using the collected data by Baum-Welch algorithm. Then the state sequence $Q = \{q_1, q_2, \cdots, q_n\}$ of the maximum observation condition probability $P(I\,|O)$ is solved through Viterbi algorithm. Thus the current motion status of vehicle can be identified according to the observable sequence with Gauss distribution density based on MGHMM model.

3.2. Vehicle rollover warning strategy based on Markov prediction algorithm

The Markov chain is a state transfer process with non-aftereffect property, which is only related to the state in the previous time, while is not related to the state in the past time. It possesses the characteristics of discrete, stochastic and non-aftereffect property. The multi-step transfer matrix $A^{(n)} = A^n$. The state of a certain time in the future can be known by calculating if the initial probability on t_0 time and the transition matrix between states are known. The MGHMM models have been established, and the state transition matrix A was also obtained, which is the probability nothing to do with time. If the vehicle is in the state of $S_i\,(i = 1, 2, 3, 4)$ now, the probability in which the state of the vehicle is at S_j in the future time t will be a_{ij}. Taking the maximum likelihood as the selection principle, i.e., the maximum value among $(a_{j1}, a_{j2}, a_{j3}, a_{j4})$ is selected as forecast result. $(a_{j1}, a_{j2}, a_{j3}, a_{j4})$ are arranged sequentially from small to large, thus the corresponding state of the largest one is the predicted state.

The predicted time of the rollover warning system must be determined in advance. The warning time is chosen as 3 seconds after taking a comprehensive consideration about the time of driver receiving the warning, triggering warning device, conducting brake operation and rollover warning calculation, and so on.

Figure 3 is the principle diagram of rollover warning. First, the simulation test is carried out on four conditions which are prone to rollover for a SUV in the Carsim. Second, the signals of roll angle and lateral acceleration are acquired and the data are segmented. Third, K-means algorithm is used to cluster the data according to the vehicle motion status. Then, the Baum-Welch algorithm is used to train the data so as to establish the MGHMMs. And then, the largest state sequence about the given observation condition probability is solved via Viterbi algorithm, so that the current state of vehicle can be identified. If the current state is driving straight ahead or steering normally, rollover warning system is in a dormant state without working. And the warning system will start to work if the current state is in steering quickly. In addition, the step size is set as 0.1 seconds, and the number of prediction steps is $N = 30$ within 3 seconds. In accordance with the principle of state multiple step transfer, the state corresponding to the maximum probability in the current prediction result will be output after each prediction step. The alarm device will be triggered if the rollover occurs within 3 seconds.

3.3. The HMM training and simulation for rollover warning

The aim of establishing HMM is to determine the parameters of each element in MGHMM model $\lambda = (\pi, A, C, \mu, U)$. At the beginning, the HMM toolbox (Hidden Markov Model Toolbox for MATLAB) [11] is loaded to MATALB. Then, the m-file program is written, and Baum-Welch algorithm is chosen to training Multi-dimensional Gauss Hidden Markov models for vehicle running states.

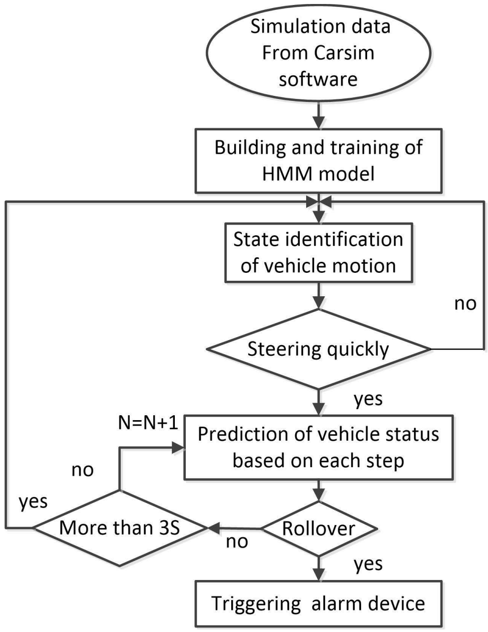

Fig. 3. Flow diagram of rollover warning

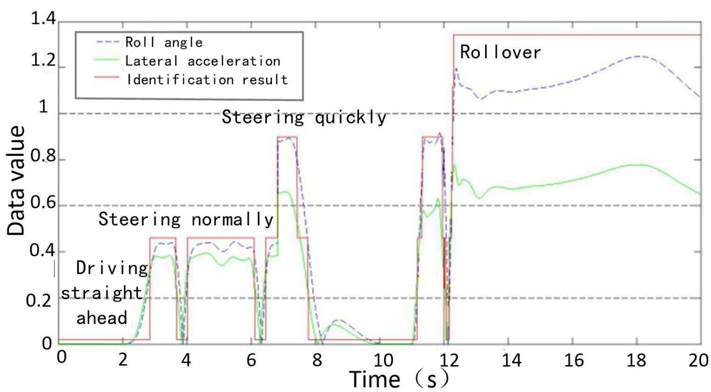

Fig. 4. Prediction results of vehicle motion status

The Viterbi algorithm is adopted to identify the motion status of the vehicle under multiple running conditions on basis of the established HMM model. The motion parameters of the vehicle are roll angle and roll acceleration. And the value of the roll angle is lessened to 60 times so that the curves of the lateral acceleration and the roll angle can be observed in one chart conveniently. The identification results are shown in Figure 4. The real line in graph represents the identification results, and each step represents a motion status among driving straight ahead, steering normally, steering quickly or rollover from low to high. Not only the identification results achieve good coverage, but also the current status can be identified exactly.

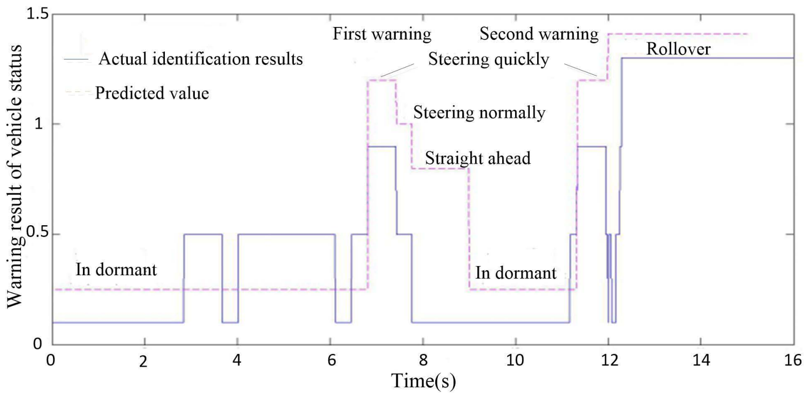

Fig. 5. Prediction result of vehicle motion status

The Hidden Markov sequence is used to conduct the simulation of rollover prediction based on the identification of the vehicle motion status under multiple running conditions. According to the scheme of rollover prediction, if the current state is identified as steering quickly, the rollover warning must be carried out. And the vehicle motion status should be predicted in the prospective 3 seconds so as to judge if the vehicle rollover will occur. And the warning device will remind the driver if the vehicle will roll over. When the vehicle is in driving straight ahead and steering normally, the warning system will no response. From the predicted results shown in Figure 5, one can see that the vehicle is in straight and normal steering status at first, so the warning system is in dormant. When the vehicle is in the steering quickly status for the first time, it is in a status of danger and the warning system is triggered timely to conduct state prediction. The forecast result shows that the vehicle rollover will not occur in the prospective 3 seconds, so the warning system enters into a dormancy, and the vehicle is in the status of driving straight ahead after the threshold of 3 seconds is over. The warning system conducts state forecast when the vehicle is in a status of steering quickly again. And the warning device is triggered when the vehicle is predicted to rollover in the prospective 3 seconds.

4. Prediction of vehicle model parameters based on HMM and ANN

HMM can be used to identify and predict the vehicle motion status in the current and the future, however, the roll angle and lateral acceleration of vehicle in the next period cannot be obtained according to the prediction results. Taking the identification and prediction results of HMM as training samples of BP neural network, the vehicle motion parameters in the next period can be accurately predicted after the BP neural network have been trained. In this way, HMM can guide ANN learning, which can not only reduce unnecessary training of ANN, but also can improve the training efficiency and prediction accuracy. If the vehicle will rollover in the prospective 3 seconds, the driver is able to observe the degree of vehicle rollover visually, in addition, the parameters of ANN prediction can be used as the input data of the electronic anti-rollover control system.

In this paper, the BP neural network is selected as the ANN model. The prediction accuracy index of Tansig function is higher, so it is chosen as the processing function of hidden layer. The auto-adapted study speed gradient descent method with momentum is chosen as training function. The number of neurons is 15. The momentum factor is chosen as 0.95 and the learning factor is chosen as 0.1 through a lot of test.

The vehicle motion parameters have been predicted in a running condition, the double lane change, to verify the data of the roll angle in the next-time-period respectively. The sim function in MATLAB is used to conduct the simulation of the BP neural network. The current motion parameters and the next-time-period motion parameters which are obtained from simulation experiments previously are taken as the training samples of BP neural network. The current motion parameters are the data in 0–3 seconds, and the data in 3–6 seconds will be predicted by simulation.

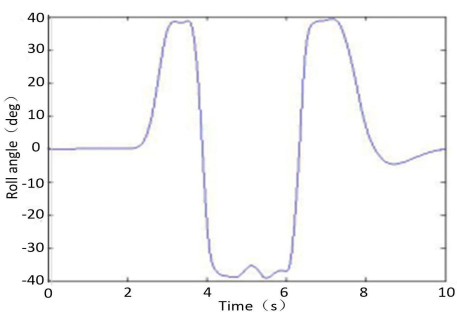

Fig. 6. The response of roll angle

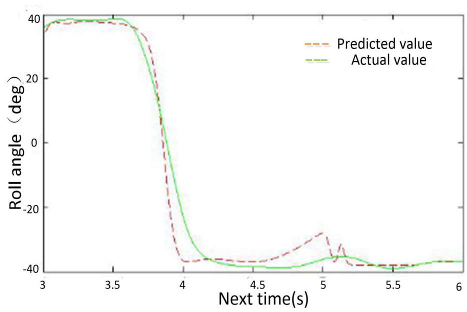

Fig. 7. Comparison between prediction and in double lane change experiment in double lane change

Figure 6 shows the test data of roll angle under the condition of double lane change. And the comparison of the roll angle in next period between the value predicted by BP neural network and the value acquired by experiments under the same conditions are shown in Figure 7. As Figure 7 shown, the predicted value of the roll angle is consistent with the actual data. It can be seen that the motion parameters in the future time can be predict effectively based on HMM and ANN.

5. Conclusion

In this paper, the roll angle and lateral acceleration are used as the observed sequence in the established Hidden Markov Model and Markov prediction algorithm, which can provide real time warning effectively. Moreover, it can forecast vehicle motion parameters by combing HMM with ANN. The training efficiency and prediction accuracy are improved by using HMM which guides the training of the neural network. The established rollover warning method not only can predict the vehicle movement status, but also can forecast specific movement parameters, which can be used by the driver to judge the rollover quantitatively as well as providing data for the anti-rollover electronic control system with less parameters and high efficiency.

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