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A Real-time Rollover Threat Index for Sports Utility Vehicles

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Abstract

In this paper, the methodology capable of computing a Time-To-Rollover (TTR) index in real-time [1] is verified by using test data of two Sports-Utility Vehicles (SUV)-a 1988 Suzuki Samurai and a 1997 Jeep Cherokee. First, simple yaw-roll models are constructed based on the test data. The TTR is computed from the simple model and then corrected by using an Artificial Neural Network. The TTR generated by the Neural Network is then verified against the data for the two test vehicles.

1. Introduction

The safety performance of passenger cars has been an important factor influencing consumers' purchasing decisions and government regulations. Currently, a New Car Assessment Program (NCAP) exists under the US Department of Transportation which assess the crash worthiness of new cars. The results are published as a well-known one-to-five star rating system indicating the crash protection for passengers within the same weight class. The final results are easy to understand and have been a valuable index for the general public. Recently, the National Highway Traffic Safety Administration (NHTSA) announced its plan to provide information about the rollover stability of vehicles in its future safety rating. One major driving force behind this new initiative is the well-publicized rollover incidents of several Sports-Utility Vehicles (SUV) and passenger cars (Suzuki Samurai, Isuzu Trooper, Mercedes A-class and the Mercedes/Swatch SmartCar). It seems fair to say that rollover stability is becoming an important element in the vehicle safety performance.

Along another line, active counter-measures to prevent rollover crashes are being pursued by research supported by NHTSA. To prevent rollover, one of the most important enabling techniques is the development of accurate rollover threat indices. A rollover warning/control algorithm will work well only if the impending vehicle rollover threat can be accurately represented. Most of the existing rollover warning algorithms [2,3,4,5,6,7] are based on acceleration or roll angle threshold values. Rakheja and Pichè proposed an early warning safety monitor in 1990 [2]. Under static cornering maneuvers, a rollover acceleration threshold is defined when the inside tire deflection reaches zero, i.e. the tire normal force becomes zero and the tire is lifting off the ground. In implementation, a warning is issued whenever the measured lateral acceleration exceeds this threshold. They also applied the same idea to define a threshold for the semi-trailer roll angle. Preston-Thomas and Woodrooffe [3] used the lateral load transfer ratio (LTR) to indicate rollover threat. LTR can vary from 0 when the loads carried by the tires are equal, to 1 when the tires lift off and the lateral acceleration reaches the rollover acceleration threshold. Freedman et al. [4] proposed a rollover advisory sign on highway exit ramps. When the velocity of the truck is higher than the advised speed limit, which is determined based on the curvature of the exit ramp, a warning light is triggered. In their research, the warning signal did not use additional information to identify each truck's rollover acceleration threshold. McGee et al. [5,6] proposed a warning system which is similar to that of [4]. However, their system detects the type, speed, weight, and height of the truck to identify the rollover acceleration threshold of each vehicle from a look-up table. Winkler et al. [7] recently proposed a rollover stability advisor (RSA) system. RSA determines the rollover acceleration threshold based on real-time measurements of the status of the vehicle. The measurement they used includes force and moment at the fifth wheel and many roll motion variables. Three acceleration threshold values are calculated dynamically to determine rollover threshold level.

Nalecz et al. proposed an energy based function named Rollover Prevention Energy Reserve (PRER) in 1987 [8,9,10]. PRER is defined as the difference between the energy needed to bring the vehicle to its tip-over position and the rotational kinetic energy, which can be transferred into the gravitational potential energy to lift the vehicle. PRER remains positive for non-rollover cases. When it becomes negative, a rollover will occur if nothing is done to take energy out of the roll mode. A special advantage of PRER is that the same concept can be applied to both maneuver induced and tripped rollover incidents.

The above-mentioned concepts were based on acceleration, roll angle or energy threshold values which are estimated from the information at a fixed time. In

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analogy, it is like taking a still picture of a dynamic system and uses the information (frozen in time) to determine the rollover threat. Apparently, a method that covers factors over a longer time horizon, particularly into the future, could give us a better perspective. Furthermore, the "distance" away from these threshold levels is not an intuitive measure. Therefore, we proposes a "Time-To-Rollover" (TTR) metric [1], which was proposed as the basis to assess rollover threat since it "counts-down" toward rollover and is an intuitive threat index. To realize this simple threat index, however, we need to construct a TTR calculation unit that can accurately predict TTR under all vehicle speed, load and steering pattern. Implementing TTR in real-time seems to involve design trade-off. On the one hand, a faster-than-real-time vehicle model is needed. For example, in order to predict a TTR of (up to) 3 seconds, one needs to predict vehicle response in the next 3 seconds repeatedly. If TTR is to be updated every 50msec, the vehicle model needs to be 60 times faster than real-time. On the other hand, the TTR predicted by this model needs to be accurate enough under all driving scenarios so that good warning decision can be made. An innovative approach was proposed in [1] to solve this dilemma.

Although the focus in [1] was on heavy trucks, it is obvious that the design procedure proposed in [1] can also be applied to SUV as well. We will maintain the basic architecture of the algorithm shown in [1] and will apply it to two SUVs. The major challenges of this seemingly straight-forward extension lie in the fact that in the previous work, the design and verification were based on simulation data, while in this work, real vehicle test data will be used.

The remainder of this paper is organized as follows: the simplified yaw-roll models identified from the vehicle test data are presented in Section 2. In Section 3, the TTR index is defined and presented. The Neural Network trained to produce "desired" TTR response is also discussed. The results of real-time rollover treat index are then presented in Section 4. Finally, conclusions are made in Section 5.

2. Modeling

A vehicle yaw-roll model needs to be constructed to compute vehicle roll motion under steering excitations. In this paper, a yaw-roll model will be obtained by fitting test data obtained on two SUVs: a 1988 Suzuki Samurai and a 1997 Jeep Cherokee. In the remainder of this paper, these two vehicles will be referred to as "Samurai" and "Cherokee", respectively. The vehicle test data was obtained from the Vehicle Research and Test Center (VRTC) of NHTSA. The test data will be used first for the vehicle model construction (see Figure 1) and later for rollover algorithm verification.

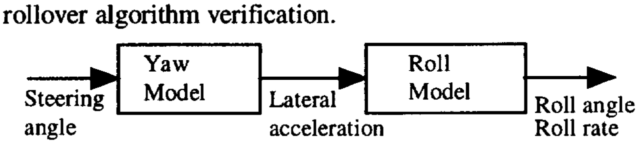

Figure 1 Structure of the simplified model

As can be seen from Figure 1, the proposed yaw-roll model is separated into a yaw and a roll part. This series arrangement may propose less-than accurate results compared with an integrated yaw-roll model. However, this simplified structure was found to be superior in two aspects: ease of model construction, and faster computations.

2.1 Yaw Model

The vehicle yaw model (see Figure 2) was assumed to be described by a linear bicycle model and the vehicle speed is assumed to be constant. It was found that when the vehicle speed varies significantly due to excessive steering/braking, a constant-speed linear model no longer matches the test data closely.

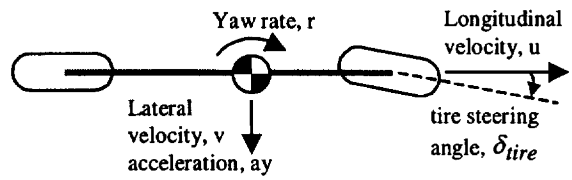

Figure 2 Yaw model (Bicycle model)

For a linear bicycle model, the discrete-time transfer function from the steering angle to lateral acceleration is known to have the following form:

$$T_{yaw}(z) = \frac{b_0 z^2 + b_1 z + b_2}{z^2 + a_1 z + a_2} = \frac{a_y}{\delta} \tag{1}$$

where a_y is the lateral acceleration and δ is the steering wheel angle which is related to the tire steering angle by a steering gear ratio. After factorization, we can get the following form.

$$T_{yaw}(z) = b_0 + k\frac{z - z_1}{(z - p_1)(z - \bar{p}_1)} \tag{2}$$

We applied standard system identification techniques to calculate k, z_1, p_1 and p_2 and then take the average of their values for multiple files of the same maneuver. These transfer functions have been found to work well under constant speed cases. When the vehicle speed varies significantly due to large steering/braking, we found it necessary to use a speed-dependent (gain-scheduled) transfer function to predict vehicle lateral acceleration accurately. A simple interpolation technique is used. As can be seen from Table 1, the lateral acceleration prediction error can be reduced significantly for steering+braking maneuvers.

Table 1 RMS values of lateral acceleration prediction errors

Ay (m/s^2)	Samurai		Cherokee	
	Const.	Braking	Const.	Braking
w/o gain-scheduling	0.3972	2.2749	0.2194	2.8197
w/ gain-scheduling	0.3660	0.6004	0.1868	0.5667

Note: Const. denotes for constant speed maneuvers.

2.2 Roll Model

The roll model was found to be well behaved and a 2 degree-of-freedom (sprung mass roll and unsprung mass roll, refer to Figure 3) model fits the test data well independent of longitudinal vehicle speeds and lateral acceleration levels. The structure of the discrete-time transfer function from lateral acceleration to sprung mass roll angle is shown as follows.

$$T_{roll}(z) = \frac{b_0 z^3 + b_1 z^2 + b_2 z + b_3}{z^4 + a_1 z^3 + a_2 z^2 + a_3 z + a_4} = \frac{\phi}{a_y} \quad (3)$$

Where ϕ is the roll angle of the sprung mass.

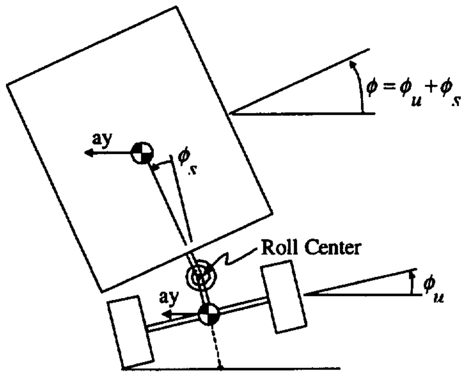

Figure 3 Roll model

Alternatively, Eq. (3) can be shown in the following form:

$$T_{roll}(z) = k\frac{(z-z_1)(z-z_2)(z-\bar{z}_2)}{(z-p_1)(z-\bar{p}_1)(z-p_2)(z-\bar{p}_2)} \quad (4)$$

where $k = \frac{(1-p_1)(1-\bar{p}_1)(1-p_2)(1-\bar{p}_2)}{(1-z_1)(1-z_2)(1-\bar{z}_2)}$. z_1, z_2 and $\bar{z}_2$ are zeros , and p_1, $\bar{p}_1$, p_2 and $\bar{p}_2$ are poles of $T_{roll}(z)$. Again, the averaged values of k, z_1, z_2, $\bar{z}_2$, p_1, $\bar{p}_1$, p_2 and $\bar{p}_2$ are taken across multiple files to obtain the final roll model.

As can be seen from Table 2, the roll angle prediction error for the Samurai is much larger than the Cherokee. A representative roll response of these two vehicles are shown in Figures 4 and 5, respectively. Under a step steering input, the roll angle of Samurai didn't reach steady-state value quickly. The roll angle keeps drifting for several seconds after the step input. This drifting may arise from either a its suspension damping or corrupted sensor. The roll angle shown in Figure 5 is derived from two optical sensor measurements installed on the right and left sides of the vehicle front bumper. It reaches a steady-state response for a step steering input quickly even under a high-g maneuver. Due to its poor roll angle measurement, the roll model identified for Samurai does not perform very well.

Table 2 RMS values of roll angle prediction errors

	Samurai	Cherokee
Roll angle (deg)	0.5926	0.1391

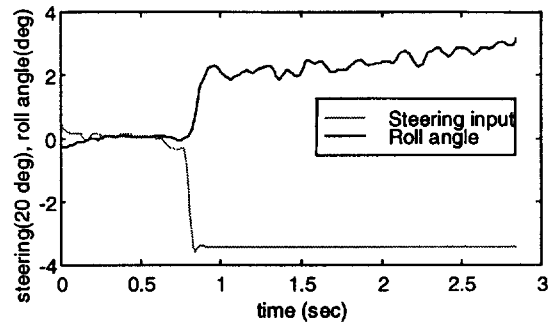

Figure 4 Roll response of Samurai (50 mph 0.4 g left turn maneuver)

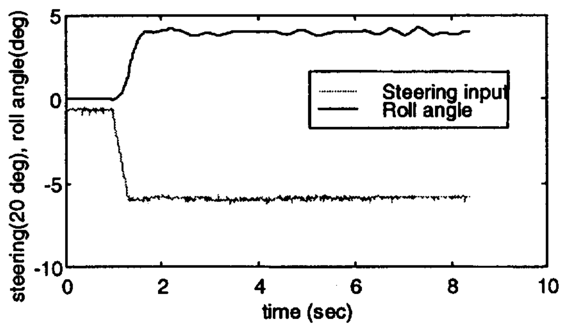

Figure 5 Roll response of Cherokee (50 mph 0.6 g left turn maneuver)

3. Time-To-Rollover (TTR) Metrics

When the vehicle roll angle exceeds a certain threshold level, wheel lift-off will occur. Since most existing passenger vehicle models were developed based on 4-wheel assumptions, the vehicle response under wheel lift-off conditions can longer be predicted accurately. In this study, we define wheel lift-off as an unacceptable rollover incident. In other words, while we use the term "rollover threat index", the index was in fact issued based on "Time-To-Wheel-lift-off". This decision will not result in any major change in the overall algorithm development. A more aggressive roll angle threshold level can be used and the overall design process to be described below will stay the same. The roll angle threshold for these two vehicles are selected to be 3 degrees (for Samurai) and 3.5 degrees (for Cherokee), respectively.

3.1 Model based TTR

From the "rollover incidents" (more precisely, wheel-lift-off incidents) detected in the test data files, a true TTR will be computed off-line. In other words, whenever the roll angle exceeds the defined threshold value, we can roll back the clock and define a point 0.2 seconds before this wheel-lift-off incident to have a "TTR" of 0.2 seconds. Ideally, if we can calculate this TTR index in real-time, the rollover threat can be accurately represented.

A model based TTR is defined as following: assuming the input (steering angle) stays fixed at its current level in the foreseeable future, the time it takes for the vehicle sprung mass to reach its critical roll angle is defined as TTR. Under normal driving conditions, TTR is usually quite large. For implementation considerations, we saturate TTR at 1 second. In other words, we will integrate the speed-dependent yaw-roll model (shown in Section 2) for up to 1 second (see Figure 6). If it is found that the vehicle does not rollover, the model-based TTR will be defined as 1 second.

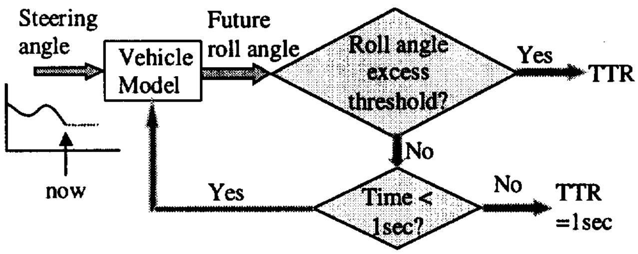

Figure 6 Flow chart for the TTR calculation

3.2 Neural Network TTR

From a previous study [1], it was found that the model-based TTR might not be accurate enough. Ideally, the predicted TTR should have a straight line of slope = -1 (on a time-TTR plot) under all driving conditions. In other words, we hope the model-based TTR gives an accurate countdown toward rollover incidents. In [1], it was proposed to use a Neural Network (NN) to correct the error between the model-predicted TTR and the true TTR. The structure of the NN is shown in Figure 7. In additional to the model predicted TTR, the NN also uses vehicle roll angle and change of roll angle to produce a corrected NN-TTR. The desired NN-TTR is the straight line (of slope = -1) as described above. In the non-rollover cases, the desired TTR will be a straight line of 1second.

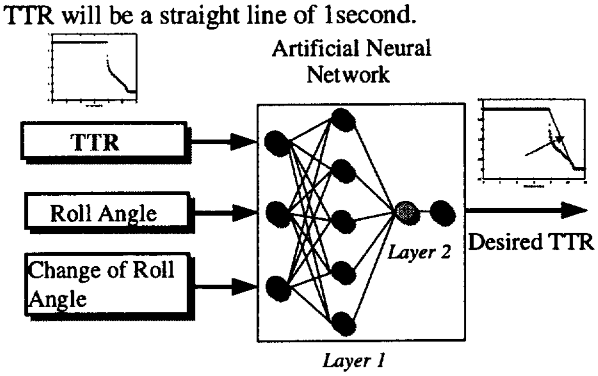

Figure 7 Input and output of the Neural Network

The NN used is quite simple. It has two hidden layers with 5 and 1 neurons, respectively. The functions of those neurons are standard tansig functions. The NN is trained for each vehicle by using test data files both with and without rollover incidents. In other words, the same NN will be used to generated a corrected TTR across all vehicle speeds and all steering and braking maneuvers.

4. System Verifications

4.1 Maneuver description for the test data

The test data from VRTC contains the following maneuvers suitable for TTR verifications: right/left steer and brake, right/left turn (no braking), double lane change, pulse steering right/left, and ramp steering right/left. These maneuvers are repeated at (nominally) constant speed of 25 and 50 mph. Usually each test condition is repeated for 10 runs. Some of the test maneuvers were done at lateral acceleration as high g as 0.6 g. There are 29 and 31 measurement channels for the Samurai and Cherokee, respectively. And more than 200 test files for each vehicle were used. As can be seen from Figure 8, some signals are noisy and contain large offsets. Therefore, these signals were processed before they are used in the verifications.

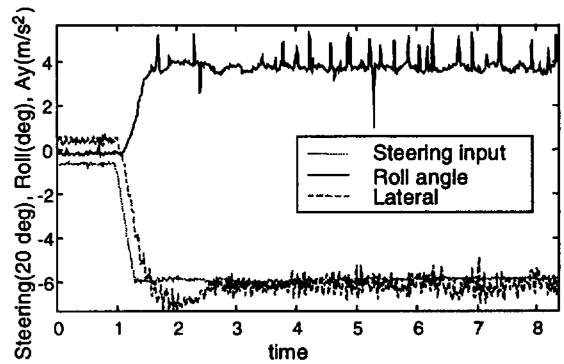

Figure 8 Required measurements for TTR calculations

4.2 TTR verification

The detail system implemented to compute a model based TTR is shown in Figure 9. The measurements required to implement this system include steering wheel angle, lateral acceleration and roll angle of the sprung mass.

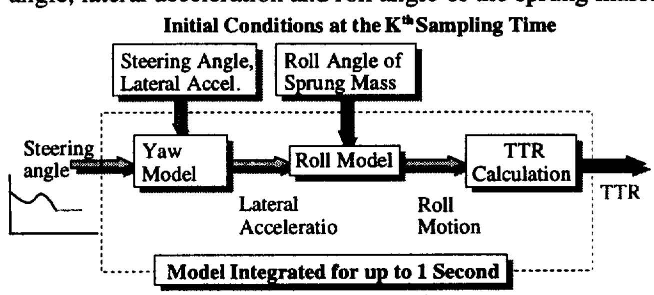

Figure 9 Detail implementation for the TTR calculation

We have verified the TTR for both rollover and non-rollover cases. Since the TTR for the non-rollover cases, we only show the rollover cases here (see Figures 10 and 11). The TTR for Samurai suddenly reduces to near zero. For the Cherokee, we can get about 0.3 seconds of "warning" before a rollover actually starts. From these two figures, it seems a lot more challenging to design a rollover warning (or control) algorithm for the Samurai since the roll motion occurs suddenly. We would like to emphasize, however, that the test data of the Samurai is not in as good a condition as those of Cherokee. Therefore, the problem exhibited in Figure 10 may not be completely due to the vehicle design. Since we are more confident with the model identified from the test data of the Cherokee, we will focus the future TTR discussion on the Cherokee data.

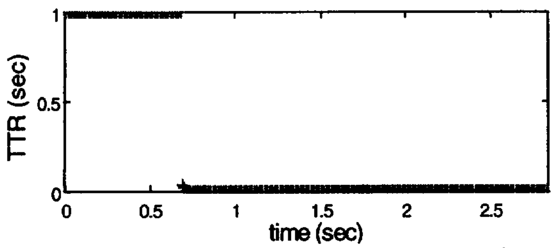

Figure 10 Model based TTR of Samurai (50 mph 0.6g right turn maneuver)

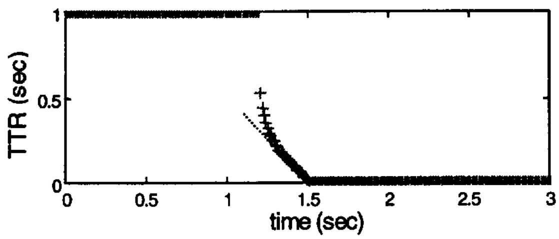

Figure 11 Model based TTR of Cherokee (50 mph 0.6g right turn maneuver)

After training the NN (Figure 7), we found that no significant improvement was obtained over the model-based TTR (refer to Figure 12). This is in contrast to the results for heavy trucks reported in [1]. In [1], the NN was found to be necessary to obtain an accurate TTR, as can be seen from Figure 13.

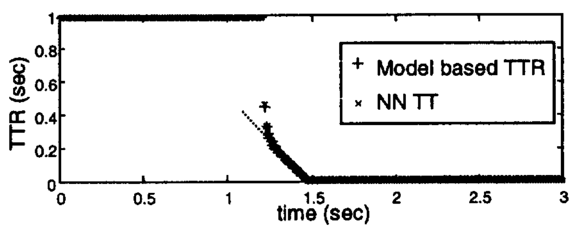

Figure 12 Model based TTR of Cherokee (50 mph 0.6g right turn maneuver)

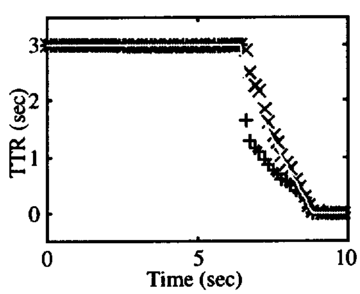

Figure 13 TTR of an M916A1/M870A2 army truck [1]. ("+": Model based TTR, "x": NN TTR).

It can be seen from Figure 12 that the NN correction may not be necessary for SUVs. Due to their lower c.g. height, the critical roll angle to denote unacceptable roll incidents (e.g., wheel lift-off) for SUV is generally much lower than that for heavy trucks. The lowered level of roll angle produces much lower TTR, i.e., the advance warning one can get to prepare for proper action is much shorter (see Figures 11 and 13, 0.3 seconds vs. 3 seconds). It seems to suggest the need for active roll-prevention controls on SUV.

5. Conclusion

A Time-To-Rollover (TTR) based rollover threat index is developed and verified by using the test data of two SUVs—a Suzuki Samurai and a Jeep Cherokee. The test data were first processed to remove noise and DC offset. The steering, lateral acceleration and roll angle data were then used to construct simple yaw-roll models. By utilizing standard gain-scheduling technique, a speed-dependent yaw model was obtained which provides a more accurate lateral acceleration prediction. It was found that the TTR computed from the simple yaw-roll model is accurate enough due to the fact the vehicle roll angles for SUV under wheel lift-off are generally very small.

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