A Genetic Algorithm Predictor for Vehicular Rollover

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***Abstract* - A model-based genetic algorithm predictor is developed to estimate the potential for vehicular rollover. The model is based on a 1997 Jeep Cherokee Sports Utility Vehicle (SUV) and is discretized at 100 Hz. Preliminary simulation results indicate rollover prediction of 400 ms in advance of the actual event. Such advance prediction would then allow the use of active anti-roll algorithms and systems such as differential braking or active suspension control.**

I. Introduction

Approximately 8.2 million Light Truck Vehicles, which include Sports Utility Vehicles (SUV) are produced yearly worldwide [1]. Currently, 120 models of SUV are offered for sale by 16 manufacturers under 28 brand names. All of these vehicles possess rollover problems. The Chevrolet/GMC Blazer has the worst record with over 55,000 rollovers last year [2]. New fatality figures show that 10,694 people died in rollovers last year and SUVs has the highest rate, by far, with 62% of all SUV deaths occurring in rollover accidents [3]. Countless lives can be saved with the introduction of rollover warning and prevention systems. Central to this effort is the development of early rollover predictor.

A number of rollover sensors have been proposed [4,5,6] but robust algorithms, which predict rollover with sufficient advance warning are still required. The present work is predicated on using such sensors [6] but extends the results in order to achieve warning sufficient to allow the use of active prevention systems such as differential braking or active suspension systems.

II. Algorithm Overview

Rollover warning systems require fast and accurate prediction of rollover threat in order to successfully interface with proactive rollover prevention systems. Prediction of the threat of rollover based on current dynamic vehicle measurements that are projected into the future may be used to define a time to rollover (TTR) index for the vehicle [7]. The TTR is the amount of time in the future that the current operating state of the vehicle, if maintained, will produce vehicle rollover (tire-lift off). Note that if the current operating conditions of the vehicle present no threat of future rollover the TTR is infinite.

The algorithm developed for this study is a model based algorithm predictor that uses a genetic algorithm predictor (GAP) to determine the system input (tire deflection) that will result in vehicle rollover approximately 50 time steps in the future assuming all other operating conditions such as vehicle speed remain constant. The input tire deflection generated by the GAP is compared to a value of the tire deflection calculated from measurements of vehicle speed as well as measurements of lateral acceleration, roll rate and roll angle at the current time step. If the calculated tire deflection equals or exceeds the value determined by the GAP then rollover may be assumed to be imminent unless preventive measures are taken.

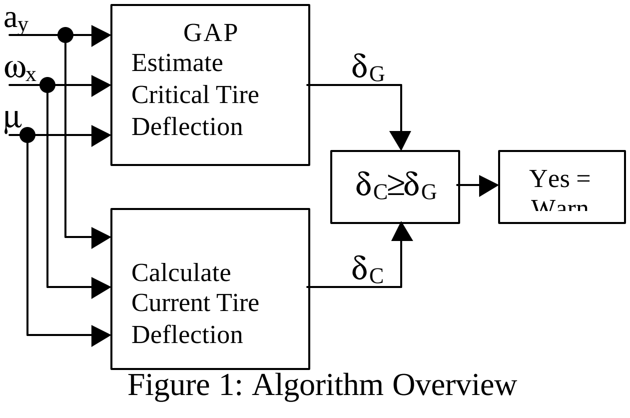

Figure 1: Algorithm Overview

A. Vehicle Model

Accurate real-time rollover prediction requires low order models that accurate predict the dynamic behavior of the vehicle under investigation. The need for model simplicity arises from the limited computational time to process the incoming measurements, determine the threat of rollover and initiate proactive measures to counter the threat. The model used in this investigation is a reduced–order three degree of freedom roll-yaw model developed by Chen and Peng [7]. The model is derived from LaGrangian dynamics and in state space form is:

$$\begin{bmatrix} I_Z & I_{XZ} & 0 \\ I_{XZ} & I_X & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{r} \\ \dot{p} \\ \dot{q} \end{bmatrix} + \begin{bmatrix} -N_r & 0 & -N_q \\ -m_r h m_0 & -L_p & -L_q \\ 0 & -1 & 0 \end{bmatrix} \begin{bmatrix} r \\ p \\ q \end{bmatrix} = \begin{bmatrix} N_d \\ 0 \\ 0 \end{bmatrix} d_t \qquad (1)$$

The definitions of the variables of Equation 1 are given below in Table 1.

I_x	Body Lateral Inertia
I_z	Body Vertical Inertia
I_{xz}	Cross Axis Inertia
p	Body Roll Rate
γ	Body Yaw Rate
θ	Body Roll Angle
δ	Front Tire Deflection Angle
N_d	Front Tire Stiffness Moment
N_r	Torsional Tire Stiffness Moment
N_θ	Tire Roll Stiffness Moment
L_p	Roll Damping Coefficient
L_q	Roll Stiffness Moment
m_r	Rolling Sprung Mass
h	Roll axis to c.g. distance
m	Vehicle Speed

Table 1: Variable Definitions

For this study it is assumed that the vehicle side-slip is negligible. The terms that comprise the matrices in Equation (1) consist of vehicle inertias and their products as well as geometric, mass, gravity and speed terms. All quantities are defined by Chen and Peng [7].

Since the matrix consisting of the vehicle inertias and product of inertias is always invertible Equation (1) may be expressed as:

$$\dot{x} = Ax + Bu \qquad (2)$$

where:

$$A = -\begin{bmatrix} I_Z & I_{XZ} & 0 \\ I_{XZ} & I_X & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} -N_r & 0 & -N_q \\ -m_r h m_o & -L_p & -L_q \\ 0 & -1 & 0 \end{bmatrix} \qquad (3)$$

and

$$B = \begin{bmatrix} I_Z & I_{XZ} & 0 \\ I_{XZ} & I_X & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} N_d \\ 0 \\ 0 \end{bmatrix} \qquad (4)$$

the state vector x consists of the vehicle yaw rate, roll rate and roll angle and the input vector u is the tire deflection. Furthermore, the continuous-time system represented by Equation 2 through Equation 4 may be discretized and expressed in state space form as:

$$x(k+1) = A_d x(k) + B_d u(k) \qquad (5)$$

where Ad and Bd are the discrete time representations of their continuous-time equivalents as defined in Equation 3 and Equation 4. For this study, the discretization of the systems was performed at 100 Hz.

B. Tire Deflection Estimate

The model of Equation 5 is driven by the input tire deflection: a quantity that is not measured. This quantity must be calculated for the current instant in time using the available measurements of speed, lateral acceleration (from which yaw rate can be derived) and roll rate and roll angle. If the side-slip of the vehicle is assumed to be negligible the yaw rate can be developed from the lateral acceleration as:

$$r = \frac{lateral\ acceleration}{speed} \quad (6)$$

where r is the vehicle yaw rate (m/s). Once the vehicle yaw rate is known it can be used in conjunction with the roll rate and roll angle measures to produce an estimate of the input tire deflection. Solving Equation 5 for the input u(k) (which is the input tire deflection δ_t):

$$\boldsymbol{d}_t \cong (B_d^t B_d)^{-1} B_d^t (x(k+1) - A_d x(k)) \quad (7)$$

The calculated value of the input tire deflection given by Equation 7 lags the actual input tire deflection by one sample period. The calculated input tire deflection will be compared to the predicted tire deflection generated by the GAP to determine the threat of rollover.

C. Genetic Algorithm Predictor

The genetic algorithm predictor (GAP) used in this study calculates the minimum allowable tire deflection 50 steps ahead based on the current speed, accelerometer and gyro measurements to meet the rollover threshold within a specified tolerance. The population used in the GAP consists of ten real-valued members, each of which represents an input tire deflection for the current iteration. Also input to the GAP are measures of the yaw rate, roll rate, roll angle and speed for the current iteration. The GAP uses the current measurements as initial conditions in the discrete time model of Equation 5 and each real-valued member of the population as an input tire deflection. The system response is projected 50 time steps ahead (500 ms) and the resulting roll angle is compared to the rollover threshold. The fitness of each individual in the population is determined by the closeness of the resulting roll angle to the rollover threshold: the closer the resulting roll angle is to the rollover threshold the more fit the individual.

The GAP employed in this study is elitist in that the best estimate of the minimum allowable tire deflection is maintained and used as the root for deriving the population for the successive generation at the next time step. The GAP population consists of ten members and the number of generations per iteration (projection 50 steps ahead) is determined by an error tolerance and is therefore variable. The crossover rate selected for the GAP is 0.7 and the mutation rate is 0.15. The high mutation rate is used prevent premature convergence of the GAP.

Intermediate recombination employing a recombination constant generated from an uniform distribution from -0.25 to 1.25 was used in the GAP to generate two sets of offspring for each pair of parents generated. The two most fit individuals from the four (the two parents and the two offspring) are maintained and reintegrated into the population for the next iteration. These steps are used in an attempt to reduce the computation time necessary for the algorithm to converge [8].

III. Simulation Parameters and Results

The parameters used in the development of the system model are given cited by Peng as being consistent with the vehicle parameters of a 1977 Jeep Cherokee [9]. The time step used for all simulations is T = 0.01s. The measurement noise associated with the gyroscope and accelerometer measures is assumed to be zero-mean Gaussian noise with variance 1e-6 rad/s and 1e-3 m/s^2 respectively. The input speed of the vehicle initially is 60 mph (26.82 m/s) and increases linearly for $4s < t < 8s$ to a maximum value of 69 mph (30.85 m/s) at t= 8 sec. For $8 < t < 12$ the input speed decreases linearly back to the original value of 60 mph at which point this value is held for the remainder of the simulation.

The rollover threshold value, the value at which rollover of the vehicle is imminent, is assumed to be 5 degrees. This scenario was used for both the cases of no rollover and a rollover threat. It is expected that the GAP estimated tire deflection will be the same in both cases since the parameters driving the GAP are the same.

1. Case I: No threat of rollover: The first case investigated involves an input tire deflection that, relative to the input speed of the vehicle, will not result in a rollover (TTR is infinite). The results of the simulation are presented below in Figure 1.

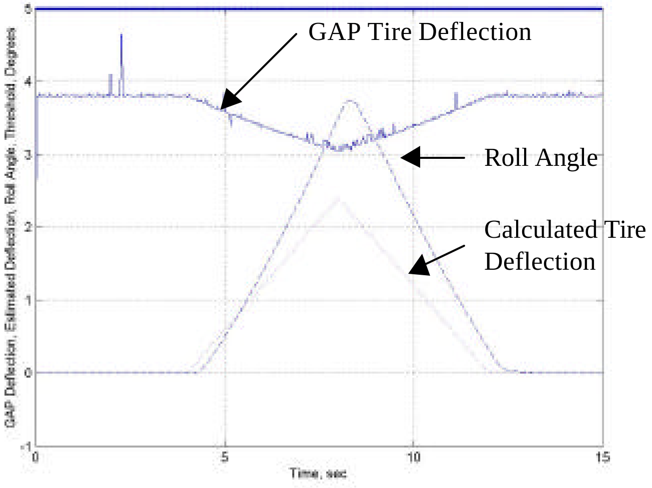

Figure 2: Case I Simulation Results – No Threat of Rollover (Infinite TTR)

The peak input tire deflection is 2.4 degrees and occurs at t = 8 sec. Note that at no time does the calculated tire deflection as determined from Equation 7 intersect the GAP minimum tire deflection curve. Based on this result the actual roll angle one should expect the actual roll angle of the vehicle to never exceed the 5 degree rollover threshold value as is demonstrated in Figure 2. Throughout the entirety of this simulation the TTR is infinite.

2. Case II: Threat of Rollover: If the actual input tire deflection is increased to a point that an intersection occurs between the GAP tire deflection and the calculated tire deflection then one should expect a crossing of the roll angle and the threshold value. In order to demonstrate this effect the actual input tire deflection used to generate the results presented in Figure 1 is doubled (to 4.8 degrees at t = 8 sec) while all other parameters remain the same. The results of this simulation are presented in Figure 3.

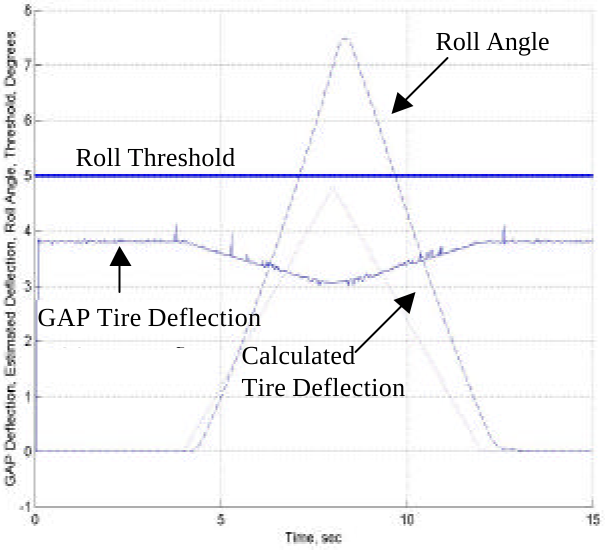

Figure 3: Case II Simulation Results. Rollover warning issued at t =6.74s.

Note that for this case an intersection of the GAP minimum tire deflection and the calculated tire deflection occurs at t = 6.74 s. This is indicative of imminent rollover if the current operating conditions are not modified to eliminate this threat. Approximately 0.4 seconds later, at t = 7.14 seconds, the roll angle threshold of 5 degrees is exceeded by the roll angle of the vehicle. The GAP, in conjunction with the calculated tire deflection provided approximately 0.4 seconds of time to initiate some preventive measures, i.e. differential braking, de-acceleration, etc. to counter the rollover threat. While this warning time is not sufficient for driver control it is more than adequate for electronic vehicle stability systems.

IV. Conclusion and Future Work

Preliminary results of the rollover warning algorithm employing a genetic algorithm model based predictor appear promising. A 400 ms warning was given for an impending rollover event. While this warning lead time is not sufficient for driver actions it is more than adequate for active stability systems using differential braking and suspension systems. Further simulations involving a variety of vehicle speeds and tire deflection inputs is warranted to insure the viability of the algorithm. Additionally, the processing time of the algorithm needs to be investigated for micro-controller implementation. Finally, the completed algorithm and associated sensor systems will be implemented in hardware and tested in vehicles.

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