Rollover Prevention Of A Heavy Vehicle Via TP Model Based $H_\infty$ Control Design Approach

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Abstract: This paper is focusing on a novel nonlinear control design approach to solve the rollover prevention problem of a heavy vehicle. To provide a heavy vehicle with the ability to resist overturning moments generated during cornering, a combined yaw–roll model including the roll dynamics of unsprung masses is studied. This model is nonlinear with respect to the velocity of the vehicle. In our model the velocity is handled as an LPV scheduling parameter. The Linear Parameter-Varying model of the heavy vehicle is transformed into a proper polytopic form by Tensor Product model transformation. The $H_\infty$ gain-scheduling based control is immediately applied to this form for the stabilization. The effectiveness of the designed controller is demonstrated by numerical simulation.

Keywords: TP, LPV, $H_\infty$ Control, Vehicle control

1. Introduction

Roll stability is determined by the height of the center of mass, the track width and the kinematic properties of the suspensions. The problem with heavy vehicles is a relatively high mass center and narrow track width. When the vehicle is changing lanes or trying to avoid obstacles, the vehicle body rolls out of the corner and the center of mass shifts outboard of the centerline, and a destabilizing moment is created.

In the literature there are many papers with different approaches on the active control of the heavy vehicles to decrease the rollover risk. Three main schemes concerned with the possible active intervention into the vehicle dynamics have been proposed: active anti roll bars, active steering and active brake. The control design is usually based on linear time invariant (LTI) models and linear approaches. The forward velocity is handled as a constant parameter in the yaw-roll model; however, velocity is an important parameter as far as roll stability is concerned [1–3].

Modern control theory mainly focuses on analysis and control design based on Linear Matrix Inequalities (LMI) and Linear Parameter Varying (LPV) system models. This
is a widespread approach to achieve guaranteed robust and efficient nonlinear control results [4, 5].

In this paper, a combined yaw-roll model including the roll dynamics of unsprung masses is studied [1]. This model is nonlinear with respect to the velocity of the vehicle. Thus, in our model velocity is handled as an LPV scheduling parameter. The controller based on this LPV model is adjusted continuously by measuring the vehicle velocity in real-time. Controller design uses modern LMI based approach to guarantee the $H_{\infty}$ gain.

The control design is based on the following steps:

1. The Linear Parameter-Varying (LPV) dynamic model of the heavy vehicle model is given.

2. We apply the Tensor Product (TP) model transformation to transform the LPV model to a TP-type convex polytopic model form. The TP model transformation is a recently proposed automatically executable numerical method. It is developed for controller design involving LPV model representation and linear matrix inequality (LMI) based control design. It is capable of numerically generate different convex polytopic forms of LPV dynamic models, whereupon LMI-based design is immediately be executable. It is important to emphasize that in many cases, the analytical derivation of these polytopic models needs very sophisticated and time consuming derivations.

3. Then we apply the LMI theorems of $H_{\infty}$ gain-scheduling to design the controller.

The paper is organized as follows: Section 2 defines the LPV model form, its representation in TP model form and shows the link to fuzzy systems. Section 3 first introduces the LPV model of the heavy vehicle and presents its TP model representations, then presents the proposed controller design method. Section 4 shows the simulation results. Finally we give a short conclusion at the end of the paper.

2. Basic Concepts

2.1. Nomenclature

- $\{a,b,\ldots\}$: scalar values;
- $\{a,b,\ldots\}$: vectors;
- $\{A,B,\ldots\}$: matrices;
- $\{A,B,\ldots\}$: tensors;
- $\mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N}$: vector space of real valued $(I_1 \times I_2 \times \cdots \times I_N)$-tensors.
• Subscript defines lower order: for example, an element of matrix $A$ at row-column number $i,j$ is symbolized as $(A)_{i,j} = a_{i,j}$. Systematically, the $i$th column vector of $A$ is denoted as $a_i$, i.e. $A = [a_1 \ a_2 \ \cdots]$.
• $(\cdot)_i,j,n, \ldots$: are indices;
• $(\cdot)_I,J,N, \ldots$: index upper bound: for example: $i = 1..I$, $j = 1..J$, $n = 1..N$ or $i_n = 1..I_n$.
• $A^+$: the pseudo inverse of matrix $A$.
• $A_{(\cdot)}$: $n$-mode matrix of tensor $\mathcal{A} \in \mathbb{R}^{l_1 \times l_2 \times \cdots \times l_n}$;
• $\mathcal{A} \times_n U$: $n$-mode matrix-tensor product;
• $\text{rank}_n(\mathcal{A})$: $n$-mode rank of tensor $\mathcal{A}$, that is $\text{rank}_n(\mathcal{A}) = \text{rank}(A_{(\cdot)})$;
• $\mathcal{A} \otimes^N_{n=1} U_n$: multiple product as $\mathcal{A} \times_1 U_1 \times_2 U_2 \times_3 \cdots \times_N U_N$;

Detailed discussion of tensor notations and operations is given in [6].

2.2. Definitions

2.2.1. Linear Parameter-Varying state-space model

Consider the following parameter-varying state-space model:

$$
\dot{x}(t) = A(p(t))x(t) + B(p(t))u(t), \tag{1}
$$

$$
y(t) = C(p(t))x(t) + D(p(t))u(t),
$$

with input $u(t)$, output $y(t)$ and state vector $x(t)$. The system matrix

$$
S(p(t)) = \begin{bmatrix} A(p(t)) & B(p(t)) \\ C(p(t)) & D(p(t)) \end{bmatrix} \in \mathbb{R}^{O \times l}
$$

is a parameter-varying object, where $p(t) \in \Omega$ is time varying $N$-dimensional parameter vector, and is an element of the closed hypercube

$$
\Omega = [a_1,b_1] \times [a_2,b_2] \times \cdots \times [a_N,b_N] \subset \mathbb{R}^N.
$$

$p(t)$ can also include some elements of $x(t)$ in which case the model is a quasi-Linear Parameter-Varying model.

2.2.2. Finite element TP model form of quasi LPV models

$S(p(t))$ is given for any parameter $p(t)$ as the combination of LTI system matrices $S_r$, $r = 1, \ldots, R$. Matrices $S_r$ are also called vertex systems. Therefore, one can define
weighting functions \( w_n(p(t)) \in [0,1] \subset \mathbb{R} \) such that matrix \( S(p(t)) \) can be expressed as parameter dependent weighted combination of system matrices \( S_r \). The explicit form of the TP model in terms of tensor product becomes:

\[
\begin{bmatrix}
\dot{x}(t) \\
y(t)
\end{bmatrix} = S \otimes_{n=1}^{N} w_n(p_n(t)) \begin{bmatrix} x(t) \\ u(t) \end{bmatrix}.
\]

Here, row vector \( w_n(p_n) \in \mathbb{R}^{I_n} n = 1, \ldots, N \) contains the one variable weighting functions \( w_{n,i}(p_n) \). Function \( w_{n,j}(p_n(t)) \in [0,1] \) is the \( j \)-th one variable weighting function defined on the \( n \)-th dimension of \( \Omega \), and \( p_n(t) \) is the \( n \)-th element of vector \( p(t) \). \( I_n (n = 1, \ldots , N) \) is the number of the weighting functions used in the \( n \)-th dimension of the parameter vector \( p(t) \). The \((N+2)\)-dimensional tensor

\[
S \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_N \times 0 \times I}
\]

is constructed from LTI vertex systems \( S_{i_1i_2 \ldots i_N} \in \mathbb{R}^{O \times I} \). Finite element TP model means that the LTI components of the model is bounded. For further details we refer to [7, 8].

### 2.2.3. Convex TP model form of qLPV model

The convex combination of the LTI vertex systems is ensured by the conditions:

**Definition 1** The TP model (3) is convex if:

\[
\forall n \in [1,N],i,p_n(t) : w_{n,i}(p_n(t)) \in [0,1];
\]

\[
\forall n \in [1,N],p_n(t) : \sum_{i=1}^{I_n} w_{n,i}(p_n(t)) = 1.
\]

This simply means that \( S(p(t)) \) is within the convex hull of the LTI vertex systems \( S_{i_1i_2 \ldots i_N} \) for any \( p(t) \in \Omega \).

### 2.2.4. Link to the TS fuzzy model

The TP model (3) is equivalent with the transfer function of the widely used type of Takagi-Sugeno (TS) fuzzy model. When we have fuzzy rules

\[
\text{IF } p_1 \text{ is } A_{1,i_1} \text{ AND } p_2 \text{ is } A_{2,i_2} \ldots \text{ AND } p_N \text{ is } A_{N,i_N} \text{ THEN } S \text{ is } S_{i_1i_2 \ldots i_N}
\]
for all combinations of $i_n = 1 \ldots I_n$ ($n = 1 \ldots N$), then the transfer function (with product sum gravity defuzzification) is

$$S(p) = \sum_{i_1=1}^{I_1} \sum_{i_2=1}^{I_2} \cdots \sum_{i_N=1}^{I_N} w_{1,i_1}(p_1)w_{2,i_2}(p_2)\cdots w_{N,i_N}(p_N)S_{i_1i_2\ldots i_N},$$

where $w_{n,i_n}(p_n)$ function is the normalized membership-function of the fuzzy antecedent $A_{n,i_n}$ and $S_{i_1i_2\ldots i_N}$ is the consequent of the rule. This model is the tensor product model which is given in (3) with a more compact notation. The convexity constraint of the previous subsection means that the antecedents form a Ruspini-partition.

2.2.5. Link to the polytopic form

In order to have a direct link between the TP model form and the polytop formula, we define the following index transformation:

**Definition 2 (Index transformation)** Let

$$S_r = \begin{pmatrix} A_r & B_r \\ C_r & D_r \end{pmatrix} = S_{i_1i_2\ldots i_N},$$

where $r = \text{ordering}(i_1, i_2, \ldots, i_N)$ ($r = 1 \ldots R = \prod_i I_i$). The function "ordering" results in the linear index equivalent of an $N$ dimensional array's index $i_1, i_2, \ldots, i_N$, when the size of the array is $I_1 \times I_2 \times \cdots \times I_N$. Let the weighting junctions be defined according to the sequence of $r$:

$$w_r(p(t)) = \prod_{n=1}^{N} w_{n,i_n}(p_n(t)).$$

By the above index transformation one can write the TP model (3) in the typical polytopic form of:

$$S(p(t)) = \sum_{r=1}^{R} w_r(p(t))S_r. \quad (6)$$

**Remark:** Note that the LTI systems $S_r$ and $S_{i_1i_2\ldots i_N}$ are the same, only their indices are modified, therefore the convex hull defined by the LTI systems is the same in both forms.
3. Control of the Heavy Vehicle

3.1. Heavy vehicle model

3.1.1. Analytic model of the heavy vehicle

Figure 1 illustrates the combined yaw-roll dynamics of the vehicle modeled by a three-body system, in which $m_s$ is the sprung mass, $m_{u,f}$ is the unsprung mass at the front including the front wheels and axle, and $m_{u,r}$ is the unsprung mass at the rear with the rear wheels and axle.

The conditions of yaw-roll model used in control design are considered. It is assumed that the roll axis is parallel to the road plane in the longitudinal direction of the vehicle at a height $r$ above the road. The location of the roll axis depends on the kinematic properties of the front and rear suspensions. The axles of the vehicle are considered to be a single rigid body with flexible tires that can roll around the center of the roll. The tire characteristics in the model are assumed to be linear. The effect caused by pitching dynamics in the longitudinal plane can be ignored in the handling behavior of the vehicle. The effects of
moving \( \ddot{\beta} + \psi \) - \( m_v \dot{h} \ddot{\phi} = \dot{Y}_d \dot{\beta} + Y_\dot{\psi} \ddot{\psi} + Y_\phi \dot{\phi} + Y_\psi \ddot{\psi} + Y_{\phi \dot{\phi}} \dot{\phi} + Y_{\psi \ddot{\psi}} \ddot{\psi} + Y_{\phi \dot{\psi}} \dot{\psi} + Y_{\psi \phi} \dot{\phi} + Y_{\phi \phi} \dot{\phi} + Y_{\psi \psi} \dot{\psi} + Y_{\phi \psi} \dot{\psi}
\)

(8)

\[
\left( I_{xx} + m_v \dot{h}^2 \right) \ddot{\phi} - I_{xx} \dot{\psi} = m_v \dot{gh} \ddot{\phi} + m_v \dot{h} \dddot{\psi} + m_v \dot{h} \ddot{\phi} + m_v \dot{h} \dddot{\phi} - k_f (\phi - \phi_{r,f}) - b_f (\phi - \phi_{r,f}) - b_r (\phi - \phi_{r,r})
\]

(9)

\[
-r \left( Y_{\beta,\phi} + Y_{\phi,\psi} + Y_{\phi,\phi} \right) = m_n v (r - h_{n,f}) (\dot{\beta} + \psi) + m_{n,f} \ddot{h}_{n,f} \phi_{r,f} - k_{r,f} \phi_{r,f} + k_f (\phi - \phi_{r,f}) + b_f (\phi - \phi_{r,f})
\]

(10)

\[
-r \left( Y_{\beta,\psi} + Y_{\phi,\psi} \right) = m_n v (r - h_{n,f}) (\dot{\beta} + \psi) - m_{n,r} \ddot{h}_{n,r} \phi_{r,r} - k_{r,r} \phi_{r,r} + k_r (\phi - \phi_{r,r}) + b_r (\phi - \phi_{r,r})
\]

(11)

aerodynamic inputs (wind disturbance) and road disturbances are also ignored. The roll motion of the sprung mass is damped by suspensions and stabilizers with the effective roll damping coefficients \( b_{s,j} \) and roll stiffness \( k_{s,j} \).

In the vehicle modeling the the lateral dynamics, the yaw moment, the roll moment of the sprung and the unsprung masses are taken into consideration. The symbols of the yaw-roll model are found in Table 1. The motion differential equations are the following.

Here, the tire coefficients are given by:

\[
Y_\beta = -(C_f + C_r) \mu, \quad N_\beta = (C_r l_r - C_f l_f) \mu,
\]

(12)

\[
Y_\phi = (C_r l_r - C_f l_f) \frac{\mu}{v}, \quad N_\phi = -(C_f l_f + C_r l_r) \frac{\mu}{v},
\]

(13)

\[
Y_{\phi,\phi} = C_f \mu, \quad N_{\phi,\phi} = C_f l_f \mu.
\]

(14)

These equations can be expressed in a state space representation. Let the state vector be the following:

\[
x = \begin{bmatrix} \beta & \psi & \phi & \dot{\phi} & \phi_{r,f} & \phi_{r,r} \end{bmatrix}^T.
\]

(15)

The system states are the side slip angle of the sprung mass \( \beta \), the yaw rate \( \psi \), the roll angle \( \phi \), the roll rate \( \phi \), the roll angle of the unsprung mass at the front axle \( \phi_{r,f} \) and at the rear axle \( \phi_{r,r} \) respectively. Then the state equation arises in the following form

\[
E(p)x = A_0(p)x + B_1(p)\delta_f + B_2(p)u,
\]

(16)

where the matrices are defined by equations (21) and (22). The parameter of the system is the forward velocity

\[
p = v.
\]

Equation (16) can be rewritten as

\[
\dot{x} = A(p)x + B_1(p)\delta_f + B_2(p)u,
\]

(17)
The $\delta_f$ is the front wheel steering angle. The control input is the difference of brake forces between the left and the right hand side of the vehicle.

$$u = \Delta F_b$$

(23)
Table 1: Symbols of the yaw-roll model

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( h )</td>
<td>height of CG of sprung mass from roll axis</td>
</tr>
<tr>
<td>( h_{u,i} )</td>
<td>height of CG of unsprung mass from ground</td>
</tr>
<tr>
<td>( r )</td>
<td>height of roll axis from ground</td>
</tr>
<tr>
<td>( \alpha_v )</td>
<td>lateral acceleration</td>
</tr>
<tr>
<td>( \beta )</td>
<td>side-slip angle at center of mass</td>
</tr>
<tr>
<td>( \psi )</td>
<td>heading angle</td>
</tr>
<tr>
<td>( \dot{\psi} )</td>
<td>yaw rate</td>
</tr>
<tr>
<td>( \phi )</td>
<td>sprung mass roll angle</td>
</tr>
<tr>
<td>( \phi_{u,i} )</td>
<td>unsprung mass roll angle</td>
</tr>
<tr>
<td>( \delta_f )</td>
<td>steering angle</td>
</tr>
<tr>
<td>( u_i )</td>
<td>control torque</td>
</tr>
<tr>
<td>( C_i )</td>
<td>tire cornering stiffness</td>
</tr>
<tr>
<td>( F_i )</td>
<td>total axle load</td>
</tr>
<tr>
<td>( R_i )</td>
<td>normalized load transfer</td>
</tr>
<tr>
<td>( k_i )</td>
<td>suspension roll stiffness</td>
</tr>
<tr>
<td>( b_i )</td>
<td>suspension roll damping</td>
</tr>
<tr>
<td>( k_{i,j} )</td>
<td>tire roll stiffness</td>
</tr>
<tr>
<td>( I_{xx} )</td>
<td>roll moment of inertia of sprung mass</td>
</tr>
<tr>
<td>( I_{xz} )</td>
<td>yaw-roll product of inertial of sprung mass</td>
</tr>
<tr>
<td>( l_z )</td>
<td>yaw moment of inertia of sprung mass</td>
</tr>
<tr>
<td>( l_x )</td>
<td>length of the axle from the CG</td>
</tr>
<tr>
<td>( l_w )</td>
<td>vehicle width</td>
</tr>
<tr>
<td>( \mu )</td>
<td>road adhesion coefficient</td>
</tr>
</tbody>
</table>

forward velocity depends on only the brake forces. The differential equation for forward velocity is

\[
m\ddot{v} = -F_{b,rl} - F_{b,rr}.
\]

3.1.2. TP model representation of the heavy vehicle model

In this section we derive the TP model of the LPV model (17) by TP model transformation. We execute the TP model transformation over \( M (M = 137) \) points grid net in the \( v \in \Omega = [40\text{km/h, 120km/h}] \) domain. We have applied the MATLAB Tensor Product Model Transformation Toolbox (TPTool) (http:\/tpool.sztaki.hu) for the TP model transformation to determine the LTI systems \((S_i)\) and the weightings \((w_i)\). The TP model transformation shows that the LPV model of the heavy vehicle model can exactly be given by the convex combination of 3 LTI vertex systems:

\[
S(p(t)) = \sum_{i=1}^{3} w_i(p(t))S_i
\]

(24)
The type of convexity considerably influences the feasibility of LMI theorems and resulting controllers control performance. In order to relax the feasibility of the LMI conditions, we define the tight convex hull of the LPV model via generating close to NO type weighting functions by the TP model transformation, see Figure 2.

**Definition 3 (NO – Normality)** Vector \( w(p) \), containing weighting functions \( w_i(p) \) is NO if they satisfy conditions (4) and (5), and the maximum values of the weighting functions are one. We say \( w_i(p) \) is close to NO if it satisfies conditions (4) and (5), and the maximum values of the weighting functions are close to one.

Its geometrical meaning is that we determine a convex hull in such a way that as many of the LTI systems as possible are equal to the \( S(p) \) over some \( p \in \Omega \) and the rest of the LTIs are close to \( S(p) \) (in the sense of \( L_2 \) norm).
3.2. Controller design

3.2.1. $H_{\infty}$ controller design

The aim of the rollover prevention is to provide the vehicle with the ability to resist overturning moments generated during cornering. Roll stability is determined by the height of the center of mass, the track width and the kinematic properties of the suspensions. The problem with heavy vehicles is a relatively high mass center and narrow track width. When the vehicle is changing lanes or trying to avoid obstacles, the vehicle body rolls out of the corner and the center of mass shifts outboard of the centerline, and a destabilizing moment is created.

In this section we utilize the above obtained convex model for the stabilization control of the heavy vehicle model. We seek an LPV controller of the form

$$\dot{x}_K = A_K(p(t))x_K + B_K(p(t))y$$
$$u = C_K(p(t))x_K + D_K(p(t))y,$$

where

$$\begin{bmatrix} A_K(p(t)) & B_K(p(t)) \\ C_K(p(t)) & D_K(p(t)) \end{bmatrix} = K(p(t)) = \sum_{i=1}^{3} w_i(p(t))K_i$$

(25)

with the same $w_i(p(t))$ weighting functions as in the model representation (24), $x_K$ is the internal state of the controller, the measured output of the model is the yaw rate and lateral acceleration so

$$y = \begin{bmatrix} \dot{\psi} \\ \dot{a}_y \end{bmatrix},$$

(26)

where the lateral acceleration can be calculated as

$$a_y = v(\dot{\beta} + \dot{\phi}) - \frac{m_s}{m} h\ddot{\phi}$$

(27)

and the control signal is given by (23). To design a suitable $K(p)$ for the given polytopic model the self-scheduled $H_{\infty}$ controller design method [9, 10] was used.

The closed-loop interconnection structure, which includes the feedback structure of the model $P$ and controller $K$, is shown in Figure 3. In the diagram, $d$, $u$, $y$ and $z$ are the disturbance, the control input, the measured output and the performance output, respectively.

A standard feedback configuration with weights strategy is illustrated in Figure 4. In the diagram $u$ is the control input, $y$ is the measured output, $z_p$ is the performance output, $z_u$ and $z_y$ are performances at the input and the output, $w$ is the disturbance, $n$ is the
The general $P - K$ structure for control design

Figure 3: The general $P - K$ structure for control design

measurement noise. The aim of the weighting function $W_p$ is to define the performance specifications. They can be considered as penalty functions, i.e. weights should be large in a frequency range where small signals are desired and small where large performance outputs can be tolerated. $W_u$ and $W_y$ may be used to reflect some restrictions on the actuator and on the output signals. The purpose of the weighting functions $W_w$ and $W_n$ is to reflect the disturbance and sensor noises. The disturbance and the performances in the general $P - K$ structure are $d = [w \ n]^T$ and $z = [z_u \ z_y \ z_p]^T$.

Figure 4: The standard feedback configuration with weights

The augmented plant includes the parameter dependent vehicle dynamics and the weighting functions, which are defined in the following form:

$$
\begin{bmatrix}
    z \\
    y
\end{bmatrix} = \mathbf{P}(\mathbf{p})
\begin{bmatrix}
    d \\
    u
\end{bmatrix}.
$$

(28)
In a Linear Parameter Varying (LPV) model $p$ denotes the scheduling variable.

The closed-loop system $M(p)$ is given by a lower linear fractional transformation (LFT) structure:

$$M(p) = F_c(P(p),K(p)),$$

(29)

where $K(p)$ also depends on the scheduling variable $p$. The goal of the control design is to minimize the induced $L_2$ norm of an LPV system $M(p)$, with zero initial conditions, which is given by

$$||M(p)||_{\infty} = \sup_{p \in \Omega} \sup_{||w||_2 \neq 0, w \in L_2} \frac{||z||_2}{||w||_2}.$$  

(30)

4. Simulation

4.1. Simulation setup

At the initial configuration of the simulation the system had a velocity of $v = 100\text{km/h}$ and all the state variables were set to zero. Then a sharp maneuver was simulated as seen in Figure 5, which describes the situation when the truck performs obstacle avoidance. The goal is to stabilize the truck by braking the rear wheels.

![Disturbance signal: Steering angle](image)

Figure 5: Disturbance signal: Steering angle
(a) Measured signal: yaw rate

(b) Forward velocity

(c) Control signal: difference of left and right brake forces

(d) Sprung mass roll angle

(e) Front unsprung mass roll angle

(f) Rear unsprung mass roll angle

Figure 6: Simulation results
4.2. Simulation results

The results can be seen on Figure 6. From the results it can be seen that the rollover likelihood can be reduced efficiently with active breaking.

From the results it can be seen that the rollover likelihood can be reduced efficiently with active breaking. The controller properties such as the magnitude of the control signal or the maximum allowed roll angle can be easily tuned by the $H_\infty$ weightings.

5. Conclusion

In this paper we investigated the rollover prevention problem for the heavy vehicle model. The novelty of this paper is that the convex polytopic representation of the vehicle model was generated by Tensor Product Model Transformation. Current approaches usually need sophisticated analytical methods to prepare the LPV system model for LMI design and neglect the importance of the convex representation. With the calculated model an LMI based $H_\infty$ gain-scheduling method was used to determine the controller to solve the rollover problem. Simulations present the performance of this controller design method.

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