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Lean and Steering Motorcycle Dynamics Reconstruction: An Unknown Input HOSMO Approach

L. Nehaoua¹, D. Ichalal¹, H. Arioui¹, S. Mammar¹ and L. Fridman²

Abstract—This paper deals with state estimation of Powered Two Wheeled (PTW) vehicle and robust reconstruction of related unknown inputs. For this purpose, we consider a unknown high order sliding mode observer (UHOSMO). First, a motorcycle dynamic model is derived using Jourdain’s principle. In a second time, we consider both the observation of the PTW dynamic states, the reconstruction of the lean dynamics (roll angle \( \phi(t) \)) and the rider’s torque applied on the handlebar. Finally, several simulation cases are provided to illustrate the efficiency of the proposed observer.

I. INTRODUCTION

In recent years, the use of powered two wheeled (PTW) vehicles is constantly growing, upsetting driving practices and road traffic. Unfortunately, this expansion is also reflected by an important increase of motorcycle’s fatalities. Recent statistics confirm this fact and consider riders as the most vulnerable road users. Several programs are launched to answer this issue and to find solutions for enhancing safety,

The success, of proposed safety systems, depends primarily on the knowledge of: 1) the dynamics of motorcycle and 2) the evolution of its states strongly involved by the rider’s action and / or the infrastructure geometry. Regarding the first issue, several studies were carried out in order to understand the motorcycle dynamics [16], [17], the stability analysis (eigenmodes) of PTW, optimal and safe trajectories [2] and the proposal of risk functions [5] to detect borderline cases of loss-of-control. These research are very few sustainable if they are not propped by a system estimating the dynamic states of the PTW.

The direct measurement, by sensors, of all the PTW states is not conceivable for two reasons: 1) instrumentation can be very expensive leading inevitably to expensive new PTW, and 2) according to used technologies, the measurement noise can seriously compromise the future safety systems. Thus, we propose to use observation techniques to overcome previous shortcomings. Within this context, including all methodologies (Luenberger, Takagi-Seguno, Extended Kalman Filter and Sliding Mode observers), very few studies exist [1], [3]. The present work proposes a robust (UHOSMO) [12], helping in states observation of motorcycle model and the reconstruction of rider’s action.

II. PROBLEM STATEMENT

Our study concerns the identification of all relevant inputs and dynamic states helping in a next stage to quantify the risk of loss-of-control when cornering. Indeed, poor cornering is responsible for most PTW accidents (single-vehicle motorcycle crashes).

To perform a safe cornering, riders should consider: 1) the appropriate speed when starting the corner, 2) the road condition (under weak friction) and 3) weather conditions do not allow optimal visibility for driving.
Early warning systems are based generally on related work carried out for standard cars [21]. The goal is the synthesis of a function giving the maximum safe speed at which a vehicle can be kept on the road while moving at a constant speed on a circular section. This speed depends, among other factors, on the lateral friction which its computing involves all the dynamic states of the bike and a good modelling of the tire-road contact. This makes the success of such warning system strongly dependent on the availability of dynamic states of the motorcycle. This challenge constitutes the contribution of our ongoing work.

III. MOTORCYCLE DYNAMICS

A. Modeling Assumptions

The study of the dynamics of motorcycle vehicles highlights two main modes of motion: in-plane mode representing the motorcycle movements in its plane of symmetry including the longitudinal motion and that of suspensions and the out-of-plane mode which describes the lateral dynamics when cornering [15], [16]. The last mode involves the roll inclination, the yaw rotation, the steering and the lateral motions of the bike. We consider here only the out-of-plane mode which describes the lateral dynamics including the longitudinal motion and that of suspensions and the tires’ spin, where its computing involves all the dynamic states of the bike and a good modelling of the tire-road contact. This speed depends, among other factors, on the availability of dynamic states of the motorcycle movements in its plane of symmetry.

By differentiating (1) and (2), the linear and the angular acceleration of $G_r$ and $G_f$ can be written for $i = r, f$ as following:

$$
\mathbf{a}_{G_i} = \frac{\partial \mathbf{v}_{oG_i}}{\partial \mathbf{t}} + \mathbf{a}_{R,G_i},
$$

$$
\mathbf{e}_{G_i} = \frac{\partial \mathbf{\omega}_{G_i}}{\partial \mathbf{t}} + \mathbf{\epsilon}_{R,G_i},
$$

where $\mathbf{a}_{G_i}$ and $\mathbf{e}_{G_i}$ are the angular velocity vector of each body, expressed in $\Re_o$, by:

$$
\omega_{G_i} = \dot{\psi}k + \dot{\varphi}i
$$

$$
\omega_{G_i} = \omega_{G_i} + \delta k_d
$$

By differentiating (1) and (2), the linear and the angular acceleration of $G_r$ and $G_f$ can be written for $i = r, f$ as following:

$$
\mathbf{M} \dot{\mathbf{\theta}} = \mathbf{Q}
$$

where the mass matrix $\mathbf{M}$ is symmetric and positive definite and obtained directly from the Jacobian matrices by:

$$
\mathbf{M} = \sum_{i=r,f} \left\{ m_i \frac{\partial \mathbf{v}_{oG_i}}{\partial \mathbf{t}} \frac{\partial \mathbf{v}_{oG_i}}{\partial \mathbf{\theta}} + \frac{\partial \mathbf{\omega}_{oG_i}}{\partial \mathbf{\theta}} I_i \frac{\partial \omega_{oG_i}}{\partial \mathbf{\theta}} \right\}
$$

$$
\mathbf{Q} = \mathbf{Q}_d + \mathbf{Q}_g + \mathbf{Q}_T + \sum_{i=r,f} \frac{\partial \mathbf{v}_{oG_i}}{\partial \mathbf{\theta}} m_i (g - \mathbf{a}_{R,G_i}) - \sum_{i=r,f} \frac{\partial \mathbf{\omega}_{oG_i}}{\partial \mathbf{\theta}} (\mathbf{I}_i \mathbf{\epsilon}_{R,G_i} + \omega_{G_i} \times I_i \omega_{G_i})
$$

In (4) and (5), $\mathbf{I}_i$ is the inertia tensor matrix, $\mathbf{Q}_d$ includes the effect of the rider’s torque and also the handlebar damping, $\mathbf{Q}_g$ represents the gyroscopic effect resulting from the tires’ spin, $\mathbf{Q}_T$ includes the effect of the tire’s sideslip force and $g$ is the gravity force vector.
C. Tire/Road Interaction and Wheels Gyroscopic Effect

To describe the tire motion, a new reference frame \( \mathcal{R}_T(c, i_T, j_T, k_T) \) is introduced at the contact point \( c \) of each wheel’s tire. \( k_T \) is the normal vector to the road surface along the \( F_z \) force.

![Tire reference frame](image)

The linear velocity vector at point location \( v \) is expressed in \( \mathcal{R}_v \) by:

\[
\begin{align*}
\mathbf{v}_{oc} &= \mathbf{v}_v + \omega_{oc} \times \mathbf{r}_{vc} \\
\mathbf{v}_{ocf} &= \mathbf{v}_v + \omega_{ocf} \times \mathbf{r}_{vcf} + \delta \mathbf{e}_s \times \mathbf{r}_{ecf}
\end{align*}
\]

(7)

From (7), the tires sideslip angles are defined by:

\[
\alpha_v = -\tan \left( \frac{j_y \cdot \mathbf{v}_{oc}}{i_y \cdot \mathbf{v}_{oc}} \right)
\]

(8)

\[
\alpha_f = -\tan \left( \frac{j_y \cdot \mathbf{v}_{ocf}}{i_y \cdot \mathbf{v}_{ocf}} \right) + \delta \cos \epsilon
\]

The equivalent tire effort at the center of each wheel is governed by:

\[
\mathbf{F}_T = \mathbf{F}_y j_T + \mathbf{F}_z k_T
\]

(9)

where \( \mathbf{F}_y = F_y(\alpha, \gamma) \) is obtained from the sideslip angle \( \alpha \) and the camber angle \( \gamma \) computed by \( \sin \gamma = \mathbf{z} \cdot k_T \).

Consequently, the contribution \( Q_T \) of the tire/road contact forces in the vector of the generalized efforts \( Q \) is given by:

\[
Q_T = \sum_{i = f, r} \left( \frac{\partial \mathbf{v}_{oc}}{\partial \theta} \right)^T F_T,i
\]

(10)

To compute the contribution of the gyroscopic effect \( Q_g \), let first write the spin velocity vector \( \omega_{s,i} \) equation of each tire in \( \mathcal{R}_v \) reference frame:

\[
\begin{align*}
\omega_{osr} &= \omega_{oc} + \dot{j}_y \\
\omega_{osf} &= \omega_{ocf} + \delta \mathbf{e}_s \times \mathbf{r}_{ecf}
\end{align*}
\]

(11)

From (3), the contribution of the gyroscopic effect in the vector of the generalized efforts \( Q \) is:

\[
Q_g = -\sum_{i = r, f} \dot{j}_y \frac{\partial \omega_{T,i}}{\partial \theta} \epsilon_{R,s,i}
\]

(12)

D. Linearized Model

The motorcycle dynamic model (4) is linearized around the straight-running trim trajectory and can be expressed by the following state-space:

\[
\dot{x}_v = A_v x_v + B_v \tau_r
\]

(13)

Here, \( x_v = [v_y, \dot{\psi}, \dot{\varphi}, \dot{\delta}, \varphi, \delta, F_{yr}, F_{yf}]^T \) denotes the state vector. \( A_v \) is a time-varying matrix related to the forward velocity \( v_y \) while \( B_v \) is a time-invariant vector. \( F_{yr} \) and \( F_{yf} \) represent respectively the tires sideslip forces introduced in the state space representing the tire relaxation.

IV. STATES AND UNKNOWN INPUTS ESTIMATION

In this section, we aim to estimate the motorcycle states and reconstruct both roll angle \( \varphi \) and rider’s torque \( \tau_r \) by using a HOSMO [12].

At first, we recall some important definitions about observability and detectability of linear systems (for proofs see [12], [19]). Consider the following SISO system, where \( x \in \mathbb{R}^n \) and \( \zeta \in \mathbb{R} \) is the unknown input:

\[
\begin{align*}
\dot{x} &= Ax + Bu + D \zeta \\
y &= Cx
\end{align*}
\]

(14)

**Definition 4.1:** In the absence of unknown input \( (\zeta = 0) \), system (14) is observable if and only if the observability matrix \( P \) such that:

\[
P = \begin{bmatrix} C \\ \vdots \\ CA^{n-1} \end{bmatrix}
\]

(15)

has the full rank. Otherwise, it is detectable if the system’s invariant zeros are stable.

**Definition 4.2:** The relative degree of the output \( y \) with respect to the unknown input \( \zeta \) is the number \( r \) such that:

\[
CA^j D = 0 \quad j = 1, \ldots, r - 2
\]

\[
CA^{r-1} D \neq 0
\]

**Definition 4.3:** In the presence of an unknown input, system (14) is strongly observable if and only if the relative degree \( r \) satisfies: \( r = \text{rank}(P) \). Otherwise, it is strongly detectable if and only if the relative degree \( r \) exists and (14) is minimum phase system. In that case, \( r \leq \text{rank}(P) \).

As previous, consider the MIMO system of the form (14), where \( x \in \mathbb{R}^n, y \in \mathbb{R}^m \) is the output vector and \( \zeta \in \mathbb{R}^m \) is the unknown input vector.

**Definition 4.4:** In the absence of unknown inputs \( (\zeta = 0) \), system (14) is observable if and only if the observability
matrix $P$ such that:

$$
P = \begin{bmatrix}
    C_1 & \cdots & C_1 A^{n-1} \\
    \vdots & \ddots & \vdots \\
    C_m & \cdots & C_m A^{n-1}
\end{bmatrix}
$$

(16)

has the full rank, where $C_i$, $i = 1, \cdots, m$ is the $i$-th row of the matrix $C$.

**Definition 4.5:** The relative degree of the output $y$ with respect to the unknown input $\zeta$ is the vector $r = [r_1, \cdots, r_m]$ such that:

$$
C_i A^s D_j = 0 \quad i, j = 1, \cdots, m, \quad s = 1, \cdots, r_i - 2
$$

$$
C_i A^{r_i - 1} D_j \neq 0
$$

and:

$$
\det \begin{bmatrix}
    C_1 A^{n-1} D_1 & \cdots & C_1 A^{n-1} D_m \\
    \vdots & \ddots & \vdots \\
    C_m A^{n-1} D_1 & \cdots & C_m A^{n-1} D_m
\end{bmatrix} \neq 0
$$

**Definition 4.6:** In the presence of an unknown input, system (14) is strongly observable if and only if the total relative degree $r_T = r_1 + \cdots + r_m$ satisfies: $r_T = \text{rank}(P)$. Otherwise, it is strongly detectable if and only if the relative degree vector $r = [r_1, \cdots, r_m]$ exists, and (14) is minimum phase.

From definition (4.1), the motorcycle dynamics (13) is neither observable nor detectable. Indeed, for all $v_x$ in the allowable velocities range, the observability index is equal to 6 which is less than the system order ($n = 8$), in addition, the motorcycle dynamics has one unstable invariant zero which makes the motorcycle dynamics to be a non-minimum phase.

A. Estimation of the Roll Angle and Rider’s Torque

In order to make the system observable, the motorcycle model (13) is rewritten such that the roll angle $\varphi$ and the steering torque $\tau_r$ are considered as unknown inputs. In fact, the unstable invariant zero is a direct consequence of the counter-steering phenomena generated by the motorcycle roll. In this case, the new system equation is written as:

$$
\dot{x}_p = A_p x_p + D_{pp} \zeta
$$

$$
y_{pp} = \begin{bmatrix}
    \delta \\
    \psi
\end{bmatrix} = C_{pp} x_p
$$

$$
D_{pp} = \begin{bmatrix}
    D_p & B_p
\end{bmatrix}
$$

(17)

where $x_p = [v_y, \dot{\psi}, \dot{\varphi}, \delta, \delta, F_{yr}, F_{yf}]^T$ denotes the state vector and matrices $A_p$, $B_p$ and $D_p$ are given by:

$$
B_p = \begin{bmatrix}
    0.016 & -0.006 & -0.019 & 0.008 \\
    0.008 & -0.019 & 0.008 & 0
\end{bmatrix}
$$

$$
D_p = \begin{bmatrix}
    -26.176 & 0.826 \\
    42.796 & 261.877 \\
    0 & 0 \\
    5437.244 v_x & 3849.877 v_x
\end{bmatrix}
$$

From definition (4.5), the output $y_{pp}$ in (17) has a relative degree vector $r = [2, 1]$ with respect to the unknown input vector $\zeta$. In addition, system (17) has 3 stable invariant zeros for all $v_x$ in the allowable velocities range. It results from (4.6), that (17) is also strongly detectable. This definition implies that only $r_T = r_1 + r_2$ system’s states can be estimated exactly while the observation of the remaining states are asymptotically exact.

As before, to estimate the system’s state $x_p$ and the unknown input vector $\zeta$, it is necessary to separate the clean states from those contaminated by the unknown inputs. To achieve this, system (17) is transformed to a new coordinates system $\xi_p = T x_p$ such that the closed-loop system dynamics $(A_p - C_{pp} L_{pp}, D_{pp}, C_{pp})$ is expressed by:

$$
\dot{\xi}_1 = \xi_2
$$

$$
\dot{\xi}_2 = A_{21} \xi_1 + A_{22} \xi_2
$$

$$
y_{pp, new}^T = [\xi_1, \xi_2]
$$

(18)

where $\xi_{pp}^T = [\xi_1^T, \xi_2^T] \in \mathbb{R}^n$ and $\xi_1^T = [\xi_{11}, \xi_{12}, \xi_{12}] \in \mathbb{R}^{r_T}$ and $\xi_2^T = [\xi_{21}, \cdots, \xi_{24}] \in \mathbb{R}^{r_{rr}}$. Next, the state observer is designed as:

$$
\dot{\hat{z}} = A_p z + L_{pp} (y_{pp} - C_{pp} \hat{z})
$$

$$
\dot{\hat{\theta}} = A_{21} \hat{\theta}_1 + A_{22} \hat{\theta}_2
$$

$$
\hat{x}_p = z + T^{-1} \hat{\theta}
$$

in which $\hat{x}_p$ is the vector of estimated states, $z \in \mathbb{R}^n$ and $\hat{\theta} \in \mathbb{R}^{r_T}$ is given by (recall that $n = 7$, $r = [2, 1]$ and $r_T = 3$):

$$
\theta = \begin{bmatrix}
    \theta_1 \\
    \theta_2
\end{bmatrix}
$$

(19)

$$
\begin{bmatrix}
    v_{1,1} \\
    v_{1,2} \\
    v_{2,1} \\
    \hat{\theta}_2
\end{bmatrix}
$$

(20)

Once again, $v_i \in \mathbb{R}^{M+k+1}$ is the nonlinear part of the observer where $i = 1, \cdots, m$ and $r_M = \max(r_i)$. Each unknown input $\zeta_{i}$ is bounded with $|\zeta_{i}| \leq \zeta_{i, \max}$ and the $(r_M - r_i + k)$ successive derivatives of $\zeta_{i}$ are bounded by the same constant $\zeta_{i, \max}$, consequently the auxiliary variable $v_i$,
is a solution of the discontinuous vector differential equation by considering \( \lambda = 1 \) as:

\[
\begin{align*}
\dot{v}_{i,1} &= -3\lambda^\frac{1}{2} |v_{i,1} - y_p + C_p z|^\frac{3}{2} \text{sign}(v_{i,1} - y_p + C_p z) + v_{i,2} \\
\dot{v}_{i,2} &= -2\lambda^\frac{1}{2} |v_{i,2} - \dot{v}_{i,1}|^\frac{3}{2} \text{sign}(v_{i,3} - \dot{v}_{i,1}) + v_{i,3} \\
\dot{v}_{i,3} &= -1.5\lambda^\frac{1}{2} |v_{i,3} - \dot{v}_{i,2}|^\frac{3}{2} \text{sign}(v_{i,3} - \dot{v}_{i,2}) + v_{i,4} \\
\dot{v}_{i,4} &= -1.1 \text{sign}(v_{i,4} - \dot{v}_{i,3}) \\
\end{align*}
\]

Finally, the reconstruction of the unknown input vector is possible by using:

\[
\begin{bmatrix}
\dot{\phi} \\
\dot{\tau}
\end{bmatrix} = \mathbf{D}^{-1} \begin{bmatrix}
\begin{bmatrix}
v_{i,3} \\
v_{i,2}
\end{bmatrix} \\
\begin{bmatrix}
a_{11,11} & \cdots & a_{12,14} \\
a_{11,21} & \cdots & a_{12,24}
\end{bmatrix} \boldsymbol{\theta}
\end{bmatrix}
\]

\[
\mathbf{D} = \begin{bmatrix}
d_{11} & d_{12} \\
d_{21} & d_{22}
\end{bmatrix}
\]

**Remark 4.1:** In the strong observability case, all system’s states are exactly estimated and the coordinates transformation matrix \( \mathbf{P} = \mathbf{T} \mathbf{x} \) is none than the observability matrix \( \mathbf{P} \). However, in the strong detectability case, only \( r \) system’s states are exactly estimated where \( r \) is the relative degree. Consequently, it is simple to show that the \( r \) first lines of the coordinates transformation matrix \( \mathbf{T} \) are the same of those of the observability matrix \( \mathbf{P} \). The expression of the remaining \( n - r \) lines are explicitly described and proven in [20].

V. SIMULATION RESULTS

In this section, the unknown input high order sliding mode observer is constructed for the presented motorcycle model. Some simulations and discussions are provided to illustrate the effectiveness and the ability of the UIHOSMO in estimating simultaneously the dynamic states and both roll angle and the applied torque by the rider on the handlebar. The observer is designed in such a way to estimate all the dynamic states and unknown inputs from only the knowledge of steering angle \( \delta(t) \) and the yaw rate \( \psi(t) \). The parameters \( \lambda_i, i = 1, 2 \) of the differentiator (21) are chosen as follows \( \lambda_1 = \lambda_2 = 10000 \). The Luenberger gain \( \mathbf{L}_{pp} \) of (25) is computed by pole placement at: \(-15, -30, -45, -60, -150, -165, -180\), and the obtained matrix is:

\[
\mathbf{L}_{pp} = \begin{bmatrix}
-254.15 & -155.92 \\
99.80 & 297.89 \\
1097.82 & 1537.85 \\
5932.04 & 7017.05 \\
208.44 & 51.40 \\
2.58 \times 10^5 & 9.16 \times 10^4 \\
1.35 \times 10^6 & 6.69 \times 10^5
\end{bmatrix}
\]

The change of coordinates matrix \( \mathbf{T} \) is given in equation (23). With these parameters and matrices, the UIHOSMO is implemented with initial conditions \( \hat{x}(0) = [0.1745 \ 0.1745 - 0.2618 - 0.0873 \ 50 \ 50 \ 0] \) and \( \hat{\phi}(0) = 0 \). These initial conditions correspond to a early cornering case with longitudinal speed at \( v_x(t) = 15 m/s \).

![Fig. 4. Actual state (solid blue line) and estimated state (dashed red line)](image1)

![Fig. 5. Actual state (solid blue line) and estimated states (dashed red line)](image2)

A. Initial Conditions

A first simulation is performed with the same initial conditions \( \hat{x}(0) = x(0) \). For different initial conditions, let
possible to deal with the problem of oscillations by parameter adjustment of the observer ($\lambda$). In this work, only the estimated states in the presence of modeling uncertainties, the observer provides accurate estimations for almost all states, only the estimations of the state variables. The effect of the uncertainties can be seen explained previously, the longitudinal velocity $v_x$ is considered constant, but in practice, it is not. The proposed observer is subjected to a time-varying $v_x \in [13.8, 15.3](m/s)$ figure 12. The estimated states in this case are illustrated in the figure 13. Notice that the observer provides an acceptable state estimation for almost all states, only the estimations of $\dot{\phi}(t)$ and $\tau(t)$ are faintly affected, in particular, in the range time $[3, 5.5](s)$ where $v_x(t) = 13.8m/s$ which is far from the nominal value of $15m/s$.

To end the simulation part, let us consider the abilities of the proposed observer in noisy measurement case. A centered random noise in the range $[-0.0001, 0.0001]$ is added to the measurements $\delta(t)$ and $\psi(t)$. The obtained results are depicted in the figure 14. The states are correctly estimated in the presence of $20\%$ variations in the parameters. As explained previously, the longitudinal velocity $v_x$ is considered constant, but in practice, it is not. The proposed observer is subjected to a time-varying $v_x \in [13.8, 15.3](m/s)$ figure 12. The estimated states in this case are illustrated in the figure 13. Notice that the observer provides an acceptable state estimation for almost all states, only the estimations of $\dot{\phi}(t)$ and $\tau(t)$ are faintly affected, in particular, in the range time $[3, 5.5](s)$ where $v_x(t) = 13.8m/s$ which is far from the nominal value of $15m/s$.

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results in figure 15 are less affected by the measurement noises and more accurate estimations are obtained.

VI. CONCLUSION

In this article, the problem of observer design for simultaneously estimating the dynamics states of a motorcycle, an unknown inputs (rider’s action) and the lateral forces on each wheel (front and rear) is considered. For that purpose, an Unknown Inputs High Order Sliding Mode observer is proposed. A motorcycle model similar to the well-known Sharp model is derived using Jourdain’s principle. The observability of the initial model is not guaranteed, then a transformation of this last into a model with two inputs by considering the unobservable state \( \phi(t) \) as an unknown input as well as the rider torque applied on the handlebar. The obtained model is then exploited to construct the Unknown Inputs High Order sliding mode observer. Some simulation results are provided in order to illustrate the efficiency of the High Order Sliding Mode Observer.
motorcycle

\[ v_x, v_y; \] longitudinal and lateral velocity
\[ \phi, \psi, \delta; \] roll, yaw and steer rotations
\[ F_r, F_p; \] rider torque
\[ A, B; \] state matrix \( A = M^{-1}E \)
\[ M; \] input matrix \( B = M^{-1}[0, 0, 0, 0, 0, 0]^T \)
\[ \dot{\phi}, \dot{\psi}; \] lateral force
\[ \phi, \psi; \] motorcycle mass matrix
\[ \delta; \] motorcycle generalized effort vector
notations
\[ x, x; \] derivatives of a variable \( x \) w.r.t time
\[ \dot{x}; \] estimate of a variable \( x \)
\[ x^T; \] transpose of vector or matrix \( x \)
\[ f_x, f_y; \] denotes front and rear

motorcycle [15]

\[ m_f, m_r; \] front and rear mass 30.63, 217.45 [kg]
\[ Z_f, Z_r; \] front tire normal force \(-1005.3\) [N]
\[ I_{fz}, I_{rz}, C_{fz}, C_{rz}; \] rear body inertia 1.23, 0.44 [kgm²]
\[ I_{sw}, I_{wz}, \cos \theta; \] wheels spin inertia 0.718, 1.051 [kgm²]
\[ R_{fz}, R_{rz}; \] wheels radius 0.304, 0.304 [m]
\[ \sigma, \gamma; \] tire’s relaxation [m]
\[ a, b, h, e, f; \] castor angle 0.4715 [rad]
\[ C_g; \] handlebar damping [N.m⁻¹.s]
\[ g; \] gravity force 9.81 [N]
\[ l; \] vehicle wheelbase [m]

\[ M = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & 0 & 0 & 0 & 0 \\ a_{22} & a_{23} & a_{24} & 0 & 0 & 0 & 0 & 0 \\ a_{33} & a_{34} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{44} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ E = \begin{bmatrix} b_{12} & b_{13} & b_{14} & 0 & 0 & 0 & 0 & 0 \\ b_{22} & b_{23} & b_{24} & 0 & 0 & 0 & 0 & 0 \\ b_{32} & b_{33} & b_{34} & 0 & 0 & 0 & 0 & 0 \\ b_{42} & b_{43} & C_g & b_{45} & b_{46} & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \]

parameters \( a_{ij} \)

\[ a_{11} = m_f + m_r \quad a_{12} = m_f k \
 a_{13} = m_h + m_f j \
 a_{14} = m_f \quad a_{22} = m_f k^2 + I_{fz} + I_{fz} \cos^2 \epsilon + I_{fz} \sin^2 \epsilon \
 a_{23} = m_f k j - C_{fz} (I_{fz} - I_{fz} \cos \epsilon \sin \epsilon) \
 a_{24} = m_f k \quad a_{33} = m_h + m_f j^2 + I_{fz} + I_{fz} \cos^2 \epsilon + I_{fz} \sin^2 \epsilon \
 a_{34} = m_f \quad a_{44} = m_f e^2 + I_{fz} \]

parameters \( b_{ij} \)

\[ b_{12} = (m_f + m_r) v_z 
 b_{13} = m_f k v_z \]
\[ b_{22} = -((I_f j_f) (R_f + i_j R_e) v_z) \quad b_{23} = (m_f + m_h + i_j R_f + i_j R_e) v_z \quad b_{24} = -i_j R_f R_e \sin \epsilon \]
\[ b_{32} = (m_f + m_h + i_j R_f + i_j R_e) v_z \quad b_{33} = m_f k \quad b_{34} = i_j R_f \cos \epsilon \]
\[ b_{42} = -m_f \quad b_{43} = Z_f \eta - m_f \quad b_{44} = Z_f \eta - m_f \eta \sin \epsilon \]
\[ b_{45} = Z_f \eta - m_f \quad b_{46} = (Z_f \eta - m_f \eta) \sin \epsilon \]

VII. APPENDIX

REFERENCES