Takagi–Sugeno Fuzzy Unknown Input Observers to Estimate Nonlinear Dynamics of Autonomous Ground Vehicles: Theory and Real-Time Verification
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Takagi–Sugeno Fuzzy Unknown Input Observers to Estimate Nonlinear Dynamics of Autonomous Ground Vehicles: Theory and Real–Time Verification

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Abstract—We address the simultaneous estimation problem of the lateral speed, the steering input and the effective engine torque, which play a fundamental role in vehicle handling, stability control and fault diagnosis of autonomous ground vehicles. Due to the involved longitudinal-lateral coupling dynamics and the presence of unknown inputs (UIs), a new nonlinear observer design technique is proposed to guarantee the asymptotic estimation performance. To this end, we make use of a specific Takagi-Sugeno (TS) fuzzy representation with nonlinear consequents to exactly model the nonlinear vehicle dynamics within a compact set of the vehicle state. This TS fuzzy modeling not only allows reducing significantly the real-time computational effort in estimating the vehicle variables but also enables an effective way to deal with unmeasured nonlinearities. Moreover, via a generalized Luenberger observer structure, the UI decoupling can be achieved without requiring a priori UI information. Using Lyapunov stability arguments, the UI observer design is reformulated as an optimization problem under linear matrix inequalities, which can be effectively solved with standard numerical solvers. The effectiveness of the proposed TS fuzzy UI observer design is demonstrated with real-time hardware-in-the-loop experiments.

Index Terms—Vehicle dynamics, nonlinear observers, vehicle state estimation, steering angle estimation, torque estimation, Takagi-Sugeno fuzzy systems.

I. INTRODUCTION

Real-time knowledge on the vehicle dynamics and the driver-related variables is essential for active safety control [1], vehicle fault detection and diagnosis [2], and driver-vehicle monitoring systems [3] of autonomous ground vehicles. Unfortunately, the onboard vehicle sensors are not always available onboard due to economical and/or technical reasons [4], [5]. In particular, within some specific situations, the human driver variables cannot be directly measured by physical sensors [6]. Hence, developing estimation algorithms to reconstruct the vehicle dynamics from the online information of low-cost sensors has received an ever-increasing interest worldwide [6]–[8].

The information on the lateral speed or the sideslip angle is a crucial index for vehicle handling and lateral stability. However, commercial physical sensors to measure the lateral speed are expensive, which cannot be directly used in practice [9]. Hence, a great deal of research efforts has been devoted to the lateral speed estimation [4], [9]–[11]. An industrially amenable kinematic-based approach has been proposed in [12]. Without requiring tire–road friction parameters or other dynamical vehicle properties, this method can lead to the drift phenomena induced by bias errors [4]. Kalman filtering methods have been widely exploited for estimating sideslip angle, especially within nonlinear estimation context [13]–[16]. Despite their effectiveness, these methods require a fine tuning task and a priori information on the noises affected to the vehicles to achieve a satisfactory estimation performance. To overcome these drawbacks, robust observers based on dynamical vehicle properties have been proposed [4], [17], [18]. However, the design of robust observers becomes challenging in presence of nonlinear dynamics and/or unknown disturbances, which is unavoidable for critical driving situations [12]. By exploiting the key features of different low-cost sensors, fusion-data-based techniques have been proved as an effective technique to estimate the vehicle sideslip angle [19]–[21]. However, such techniques induce additional sensor costs and complexities for estimation algorithms [12]. It is important to emphasize that the longitudinal-lateral coupling has been ignored in most of model-based estimation methods [13]. The main reason is due to the challenges involved in the corresponding nonlinear observer design [10].

Since the steering angle directly controls the vehicle direction, this variable is a fundamental input for path tracking control, path planning, active safety control and also detection of driver failure of intelligent vehicles [1], [22]. The steering angle can be precisely measured with absolute rotary encoders, which are quite expensive and fragile to most of passenger vehicles [10]. The low-cost sensors may lead to faulty measurement results or provide erroneous steering signals. Hence, the estimation of the steering angle has attracted increasing research attention. Based on the information from the global positioning system (GPS) and the micro-electromechanical
system (MEMS), an unscented Kalman filter has been proposed in [23] to estimate the steering angle for agricultural tractors. A linear extended observer has been proposed in [24] for steering angle estimation, which is then exploited to reconstruct the road curvature signal for vehicle lateral control. The effective engine torque is also crucial for various automotive applications, e.g., brake torque control, speed control, adaptive cruise control [25]. However, it is difficult to directly measure this vehicle variable for commercial cars due to both economic and technical reasons [26]. Then, the effective engine torque is generally supplied in the form of look-up-tables (LUTs) as a function of in-cylinder air flow rate, engine speed, injected fuel, etc., which are established and calibrated tables (LUTs) as a function of in-cylinder air flow rate, engine speed, injected fuel, etc., which are established and calibrated by steady-state engine tests [26], [27]. To reduce the costs for development, testing, maintenance, and robustness related to LUTs-based estimations, various model-based algorithms have been developed to estimate the effective engine torque. High-order sliding mode observer has been proposed in [28] to estimate the engine friction torque and load torque. Based on the principles of Kalman filtering, a method has been developed in [29] for estimating the engine combustion torque. A two-step observer design, requiring different intake air measurement sensors and real-time engine speed, has been proposed to estimate the real-time engine torque [30]. Na et al. [31] have proposed an unknown input observer for online estimation of unknown effective engine torque with measured engine speed, load torque and air mass flow rate.

Despite significant advances on vehicle estimation techniques, simultaneous estimation of both the sideslip angle and the steering angle as well as the effective engine torque has not been achieved. The significance of such an estimation solution is multi-fold. First, the estimated sideslip angle can be used for vehicle active safety control [1], while the estimates of the steering angle and the effective engine torque are useful for fault diagnosis of intelligent automotive systems [2]. Second, the proposed estimation solution is cost-effective since it only requires the online information from low-cost sensors. These issues motivate the new observer design method in this paper. The proposed unknown input (UI) observer design is based on a combined longitudinal-lateral vehicle model, whose steering angle and effective engine torque are considered as UIs. Two design challenges arise concerning: (1) dealing with the unmeasured nonlinearities of vehicle dynamics, (2) guaranteeing an asymptotic convergence of both the vehicle state and the UIs. To meet similar challenges, Takagi-Sugeno (TS) fuzzy model-based techniques [32], [33] have been attempted to design nonlinear UI observers [10], [34]. However, based on the Lipschitz property of the membership functions (MFs), the existing results generally lead to over-conservative results or complex observer design frameworks [35]. Note also that due to technical challenges related to dealing with unmeasured MFs, fuzzy UI observer design and fuzzy fault detection/diagnosis have been mainly focused on systems with measurable nonlinearities [34], which is not the case of the considered nonlinear vehicle dynamics. The following contributions of this paper can overcome the above-mentioned drawbacks.

- The nonlinear vehicle system is equivalently rewritten in a specific TS fuzzy form with both measured and unmeasured nonlinear consequents. Hence, the number of TS local subsystems, directly related to the real-time computational cost, can be significantly reduced [36]. Moreover, this TS fuzzy form permits an effective application of the differential mean value theorem [37] to deal with unmeasured nonlinearities.
- Using a generalized Luenberger observer structure, an effective UI decoupling can be achieved. Hence, an asymptotic estimation convergence of both the vehicle state and UIs can be guaranteed via Lyapunov stability without requiring any a priori UI information [34] or any specific choice of UI matrix [10]. The UI observer design is recast as a convex optimization problem under linear inequality (LMI) constraints, effectively solved with standard numerical solvers.
- The effectiveness of the proposed fuzzy UI observer framework is practically verified with real-time hardware-in-the-loop (HiL) experiments.

**Notation.** The set of nonnegative integers is denoted by \( \mathbb{Z}_+ \) and \( \mathcal{I}_r = \{1, 2, \ldots, r\} \subset \mathbb{Z}_+ \). For \( i \in \mathcal{I}_r \), we denote \( \xi_r(i) = [0, \ldots, 0, 1, 0, \ldots, 0]^\top \in \mathbb{R}^r \) a vector of the canonical basis of \( \mathbb{R}^r \). For a vector \( x, y \in \mathbb{R}^n \), the convex hull of these vectors is denoted as \( \text{co}(x, y) = \{ \lambda x + (1 - \lambda) y : \lambda \in [0, 1] \} \). For a matrix \( X, X^\top \) denotes its transpose, \( X > 0 \) means \( X \) is positive definite, and \( \text{He}X = X + X^\top \). When the existence is guaranteed, \( X^+ \) denotes the Moore–Penrose pseudo-inverse of matrix \( X \), i.e., \( X^+ = (X^\top X)^{-1} X^\top \). \text{diag}(X_1, X_2) \) denotes a block-diagonal matrix composed of \( X_1, X_2 \). \( I \) denotes the identity matrix of appropriate dimension. In block matrices, the symbol ‘\( \ast \)’ stands for the terms deduced by symmetry. Arguments are omitted when their meaning is clear.

### II. Vehicle Modeling and Problem Formulation

This section presents the nonlinear vehicle model used for UI observer design. Then, the related observer problem is formulated. The vehicle nomenclature is given in Table I.

**Table I**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( M )</td>
<td>Vehicle mass</td>
<td>1476 [kg]</td>
</tr>
<tr>
<td>( I_f )</td>
<td>Distance from gravity center to front axle</td>
<td>1.13 [m]</td>
</tr>
<tr>
<td>( I_c )</td>
<td>Distance from gravity center to rear axle</td>
<td>1.49 [m]</td>
</tr>
<tr>
<td>( I_e )</td>
<td>Effective longitudinal inertia</td>
<td>442.8 [kgm^2]</td>
</tr>
<tr>
<td>( I_y )</td>
<td>Vehicle yaw moment of inertia</td>
<td>1810 [kgm^2]</td>
</tr>
<tr>
<td>( C_{f1} )</td>
<td>Front cornering stiffness</td>
<td>57000 [N/rad]</td>
</tr>
<tr>
<td>( C_{r1} )</td>
<td>Rear cornering stiffness</td>
<td>59000 [N/rad]</td>
</tr>
<tr>
<td>( C_{a1} )</td>
<td>Longitudinal aerodynamic drag coefficient</td>
<td>0.35 [-]</td>
</tr>
<tr>
<td>( C_{a2} )</td>
<td>Lateral aerodynamic drag coefficient</td>
<td>0.45 [-]</td>
</tr>
</tbody>
</table>

#### A. Nonlinear Vehicle Model

Fig. 1 depicts a two degrees-of-freedom vehicle model. This model represents the vehicle motion in the horizontal plane,
whose dynamics is described as follows [38]:

\[
\begin{align*}
\dot{v}_x &= \frac{T_{eng} - C_x v_x^2}{I_e} + v_y r, \\
\dot{v}_y &= F_{yf} + F_{yr} - C_y v_y^2 - v_x r, \\
\dot{r} &= l_f F_{yf} - l_r F_{yr} / I_z,
\end{align*}
\]

(1)

where \(v_x\) is the vehicle longitudinal speed, \(v_y\) is the lateral speed, \(r\) is the vehicle yaw rate, and \(T_{eng}\) represents the torque input for the vehicle longitudinal dynamics [1]. The cornering forces at the front tires \(F_{yf}\) and at the rear tires \(F_{yr}\) are modeled using the magic formula [7] as

\[
F_{yi}(\alpha_i) = D_i \sin(\nabla_i), \quad i \in \{f, r\}
\]

\[
\nabla_i = C_i \arctan\{ (1 - E_i) B_i \alpha_i + E_i \arctan(B_i \alpha_i) \},
\]

(2)

where the Pacejka parameters \(B_i, C_i, D_i\) and \(E_i\) depend on the characteristics of the tire, the road and the vehicle operating conditions. Note that the Pacejka tire model (2) is used for simulation validation purposes in Section IV. The wheel slip angles for the front and rear tires are modeled as follows [1]:

\[
\alpha_f = \delta - \arctan\left( \frac{v_y + l_f r}{v_x} \right), \quad \alpha_r = \arctan\left( \frac{l_r r - v_y}{v_x} \right),
\]

where \(\delta\) is the front wheel steering angle.

Due to the practical unavailability of \(v_y\), the MFs \(h_i(z)\) of the TS fuzzy model (7), for \(i \in \mathcal{I}_a\), are not given here for brevity. Similar TS fuzzy representations as (7) have been used for vehicle dynamics estimation, see for instance [10]. However, this classical TS fuzzy form (7) leads to both theoretical and practical difficulties [35].

- Due to the practical unavailability of \(v_y\), the MFs \(h_i(z)\), for \(i \in \mathcal{I}_a\), are unmeasured. Designing TS fuzzy observers in this situation still remains challenging [35], especially in presence of unknown inputs [10].
- The classical TS model (7) may yield a TS fuzzy observer with complex structure for real-time implementation.

To overcome these drawbacks, we reformulate the vehicle system (4) in the following form:

\[
\begin{align*}
\dot{x} &= A_v(x)x + D_v d, \\
y &= C x,
\end{align*}
\]

(8)

where \(x = [v_x \ v_y \ r]^T\) is the vehicle state vector, \(d = [T_{eng} \ \delta]^T\) is the control input. The state-space matrices of the nonlinear vehicle model (4) are given by

\[
A_v(x) = \begin{bmatrix}
a_{11} & 0 & v_y \\
0 & a_{22} & 0 \\
a_{32} & 0 & a_{33}\end{bmatrix}, \quad D_v = \begin{bmatrix}
d_{11} & 0 \\
0 & d_{22} \\
0 & d_{32}\end{bmatrix},
\]

with

\[
\begin{align*}
a_{11} &= -C_x v_x, \\
d_{11} &= 1 / I_e \\
a_{22} &= -2(C_f + C_r) v_y / M, \\
a_{23} &= 2(C_f r - C_f l_f) / M v_x, \\
a_{32} &= 2(C_f l_f^2 + C_r l_r^2) / I_z v_x, \\
d_{22} &= 2C_f / I_z,
\end{align*}
\]
where $\phi(x) = v_y^2$, and

$$A(\xi) = \begin{bmatrix}
0 & r \\
0 & -2(C_t + C_r) \\
0 & \frac{2(C_r M_{xy} - C_t M_{yx})}{I_x v_y} \\
0 & \frac{2(C_r M_{xy} - C_t M_{yx})}{I_x v_y}
\end{bmatrix}, \quad \xi = \begin{bmatrix} v_x \\ r \\ \end{bmatrix},$$

$$f_v(\xi) = \begin{bmatrix}
-\frac{C_s v_x^2}{2(C_r M_{xy} - C_t M_{yx})} - v_x r \\
-\frac{C_s v_x^2}{2(C_r M_{xy} - C_t M_{yx})} - v_x r
\end{bmatrix}, \quad G_v = \begin{bmatrix} 0 \\ -\frac{C_s}{M} \end{bmatrix}. $$

In this paper, we perform the observer design in the discrete-time domain for real-time implementation. To this end, Euler’s discretization method, with the sampling time $T_s = 0.01$ s, is used to obtain the discrete-time model of system (8) as

$$x_{k+1} = A(\xi_k)x_k + Dd_k + f(\xi_k) + G\phi(x_k),$$

$$y_k = Cx_k,$$

where

$$A(\xi_k) = T_s A_r(\xi_k) + I, \quad G = T_s G_v,$$

$$f(\xi_k) = T_s f_v(\xi_k), \quad D = T_s D_v.$$  

For convenience of presentation, we explicitly denote $A(\xi) = A(V_z, r)$ with $V_z = \frac{1}{T_s} \in [V_x, V_y]$. Using the sector nonlinearity approach [32] with the premise vector $\xi \in \mathbb{R}^2$, the following four-rule TS model of system (9) can be derived:

$$x_{k+1} = \sum_{i=1}^{4} h_i(\xi_k)A_i x_k + Dd_k + f(\xi_k) + G\phi(x_k),$$

$$y_k = Cx_k,$$

where the local matrices $A_i$, for $i \in \mathcal{I}_4$, are given by

$$A_1 = A(V_z, r), \quad A_2 = A(V_z, r),$$

$$A_3 = A(V_z, r), \quad A_4 = A(V_z, r).$$

The corresponding membership functions $h_i(\xi_k)$, for $i \in \mathcal{I}_4$, of the TS fuzzy model (10) are defined as

$$h_1(\xi) = \Omega_{\xi_1} \Omega_{\xi_2}, \quad h_2(\xi) = \Omega_{\xi_1} \Omega_{\xi_3},$$

$$h_3(\xi) = \Omega_{\xi_2} \Omega_{\xi_1}, \quad h_4(\xi) = \Omega_{\xi_2} \Omega_{\xi_1},$$

with

$$\Omega_{\xi_1} = \frac{V_y}{V_x - V_y}, \quad \Omega_{\xi_2} = \frac{V_x}{V_y - V_x},$$

$$\Omega_{\xi_1} = \frac{r - r}{r - r}, \quad \Omega_{\xi_2} = \frac{r - r}{r - r}.$$

Remark 1. The reformulated vehicle model (8) has two features deserving particular attention. First, the unmeasurable nonlinearity is isolated in $\phi(x_k)$. Then, the membership functions $h_i(\xi_k)$, for $i \in \mathcal{I}_4$, defined in (11), of the TS fuzzy model (10) only depend on the measured premise vector $\xi_k$. Hence, these membership functions can be directly used to construct the UI observer structure as in (16). Note that using the classical TS fuzzy modeling, the membership functions $h_i(\xi)$, for $i \in \mathcal{I}_8$, of the TS fuzzy model (7) cannot be directly incorporated into the UI observer structure due to their dependency on the unmeasured lateral speed $v_y$. This induces major technical challenges in designing effective UI observers for systems with unmeasured nonlinearities [10]. Second, a part of nonlinearities are retained in the measured consequent $f(\xi_k)$ and unmeasured consequent $\phi(x_k)$. Hence, the resulting TS observer can be of much simpler structure, i.e., with only four fuzzy rules in place of eight-rule conservative TS representation (7). As shown in the next section, these features enable an effective framework for TS fuzzy UI observer design in terms of dealing with unmeasured nonlinearities and complexity reduction.

This paper provides an effective algorithm for the following vehicle dynamics estimation problem.

**Problem 1.** Consider the vehicle nonlinear model (10) with the compact set $\mathcal{D}_x$ defined in (5). Design an UI observer such that the lateral speed $v_y$, the steering action $\delta$ and the engine torque $T_{eng}$ can be asymptotically and simultaneously estimated from the output information (6).

### III. UI OBSERVER DESIGN FOR TS Fuzzy Systems with Unmeasured Nonlinear Consequents

This section presents a new framework to design UI observers for a generalized class of TS fuzzy systems.

#### A. Observer Structure and Useful Lemmas

For generality, we consider the TS fuzzy system (10) in a more general form

$$x_{k+1} = A(h)x_k + Dd_k + f(\xi_k, u_k) + G(h)\phi(x_k, u_k),$$

$$y_k = Cx_k,$$

where $x_k \in \mathcal{D}_x \subseteq \mathbb{R}^n$ is the state vector, $u_k \in \mathcal{D}_u \subseteq \mathbb{R}^n$ is the known input, $d_k \in \mathbb{R}^n$ is the unknown input, $y_k \in \mathbb{R}^n$ is the output vector, and $\xi_k \in \mathbb{R}^n$ is the vector measured premise variables. The nonlinear functions $f : \mathcal{D}_x \times \mathcal{D}_u \rightarrow \mathbb{R}^n$ and $\phi : \mathcal{D}_x \times \mathcal{D}_u \rightarrow \mathbb{R}^n$ are differentiable with respect to the state $x_k$. The elements of function $f(\cdot)$ are measurable whereas those of $\phi(\cdot)$ cannot be measured from the output. The state-space matrices of system (12) are given by

$$[A(h) \quad G(h)] = \sum_{i=1}^{N} h_i(\xi_k) [A_i \quad G_i].$$

Note that the MFs satisfy the following convex sum property:

$$\sum_{i=1}^{N} h_i(\xi_k) = 1, \quad 0 \leq h_i(\xi_k) \leq 1, \quad \forall i \in \mathcal{I}_N. \quad (13)$$

Let $\mathcal{H}$ be the set of membership functions satisfying (13), i.e., $h = [h_1(\xi_k), h_2(\xi_k), \ldots, h_r(\xi_k)]^T \in \mathcal{H}$. The following assumptions are considered for the TS fuzzy system (12).

**Assumption 1.** The differentiable function $\phi(x_k, u_k)$ satisfies the following boundedness condition:

$$\rho_{ij} = \min_{\rho \in \mathcal{D}_x \times \mathcal{D}_u} \left( \frac{\partial \phi(i)}{\partial x_j}(\rho) \right), \quad \bar{\rho}_{ij} = \max_{\rho \in \mathcal{D}_x \times \mathcal{D}_u} \left( \frac{\partial \phi(i)}{\partial x_j}(\rho) \right),$$

with

$$\rho_{ij} \leq \frac{\partial h_i}{\partial x_j}(x, u) \leq \bar{\rho}_{ij}, \quad (14)$$

Note that the state $x_k$ and the input $u_k$ of engineering systems are always physically bounded, i.e., $x_k \in \mathcal{D}_x$ and $u_k \in \mathcal{D}_u$. Then, the bounds $\rho_{ij}$ and $\bar{\rho}_{ij}$ in (14) can be easily computed.
Assumption 2. We assume that
\[
\text{rank}(CD) = \text{rank}(D),
\]
(15a)
\[
\text{rank} \begin{bmatrix} I & D \\ C & 0 \end{bmatrix} = n_x + n_d.
\]
(15b)
The rank conditions in (15) are standard in UIO design framework for unknown input decoupling [10], [34], [39], [40]. Note that the vehicle nonlinear system (10) verifies these rank conditions.

For estimation purposes, we consider the following UI observer structure:
\[
\begin{align}
\zeta_{k+1} &= \mathcal{T} \hat{\Phi}_k + \mathcal{L}(h)(y_k - \hat{y}_k), \\
\hat{x}_k &= \zeta_k + \mathcal{N} y_k, \\
\hat{d}_k &= (CD)^\dagger (y_{k+1} - C\hat{\Phi}_k),
\end{align}
\]
(16a)
(16b)
(16c)
with \( \hat{\Phi}_k = A(h)\hat{x}_k + f(\xi_k, u_k) + G(h)\phi(\hat{x}_k, u_k). \) The existence of the Moore–Penrose pseudo-inverse matrix \((CD)^\dagger\) is guaranteed by condition (15a). The matrices \( \mathcal{T} \in \mathbb{R}^{n_x \times n_x}, \mathcal{N} \in \mathbb{R}^{n_x \times n_y} \) and \( \mathcal{L}(h) \in \mathbb{R}^{n_y \times n_y} \) are to be designed
\[
\mathcal{T} + \mathcal{N} C = I.
\]
(17)
Remark 2. Note that selecting \( \mathcal{T} = I \) and \( \mathcal{N} = 0 \), the UI observer structure (16) reduces to the well-known Luenberger observer [41], widely used in the literature.

From the matrix constraint (17), it follows that
\[
x_{k+1} = \mathcal{T} x_{k+1} + \mathcal{N} C x_{k+1} = \mathcal{T} x_{k+1} + \mathcal{N} y_{k+1}.
\]
(18)
Then, from (12) and (18), the dynamics of the TS fuzzy system can be rewritten as
\[
x_{k+1} = \mathcal{T} A(h)x_k + \mathcal{T} D d_k + \mathcal{T} f(\xi_k, u_k) + \mathcal{T} G(h)\phi(x_k, u_k) + \mathcal{N} y_{k+1}.
\]
(19)
Let us define the state estimation error as \( e_k = x_k - \hat{x}_k \). To achieve an asymptotic state estimation, we impose
\[
\mathcal{T} D = 0.
\]
(20)
Then, the estimation error dynamics can be defined from (16a), (16b), (19) and (20) as
\[
e_{k+1} = x_{k+1} - \hat{x}_{k+1} = x_{k+1} - \zeta_{k+1} - \mathcal{N} y_{k+1} = \mathcal{T} A(h) x_k + \mathcal{T} D d_k + \mathcal{T} f(\xi_k, u_k) + \mathcal{T} G(h)\phi(x_k, u_k) + \mathcal{T} \mathcal{N} y_{k+1} = \mathcal{T} A(h) e_k + \mathcal{T} G(h)\phi(\xi_k, u_k) + \mathcal{N} y_{k+1},
\]
(21)
where \( \phi(\xi_k, u_k) - \phi(\hat{x}_k, u_k) \). The mismatching nonlinear term \( \phi \) caused by the unmeasured premise variables leads to technical difficulties in designing TS fuzzy observers [35]. To effectively deal with this term and achieve an asymptotic error convergence, the following lemma is useful to rewrite \( \delta_\phi \) as a function of \( e_k \).

Lemma 1 (Differential Mean Value Theorem [37]). Let \( g(x) : \mathbb{R}^{n_x} \rightarrow \mathbb{R}^q \) and \( a, b \in \mathbb{R}^{n_x} \). If \( g(x) \) is differentiable on \( \text{co}(a, b) \), then there exist constant vectors \( c_i \in \text{co}(a, b) \), \( c_i \neq a, c_i \neq b \), for \( \forall i \in I_q \), such that
\[
g(a) - g(b) = \left( \sum_{i=1}^{q} \sum_{j=1}^{n_x} \sigma_q(i) \sigma_{n_x}(j) \frac{\partial g_i}{\partial x_j}(c_i) \right) (a - b).
\]
(22)
Applying Lemma 1 to function \( \phi(x_k, u_k) \), then there exist \( \bar{\delta}_i \in \text{co}(x_k, \hat{x}_k) \), for \( i \in I_n \), such that
\[
\delta_\phi = \left( \sum_{i=1}^{n_o} \sum_{j=1}^{n_y} \sigma_{n_o}(i) \sigma_{n_y}(j) \frac{\partial \phi_i}{\partial x_j}(\bar{\delta}_i, u) \right) (x_k - \hat{x}_k).
\]
(22)
We denote \( \theta_{ij} = \frac{\partial \phi_i}{\partial x_j}(\bar{\delta}_i, u) \), for \( (i, j) \in I_n \times I_n \), and
\[
\theta = \left[ \theta_{11}, \ldots, \theta_{1n_x}, \ldots, \theta_{n_x n_x} \right].
\]
Due to the boundedness condition (14), the unknown parameter \( \theta \) belongs to a bounded convex set \( \mathcal{Y}_\theta \), whose set of \( 2^{n_o n_x} \) vertices is given by
\[
\mathcal{Y}_\theta = \{ \theta = [\theta_{11}, \ldots, \theta_{1n_x}, \ldots, \theta_{n_x n_x}] : \theta_{ij} \in \{ \rho_{ij}, \overline{\rho}_{ij} \} \},
\]
where the bounds \( \rho_{ij} \) and \( \overline{\rho}_{ij} \) are given in (14). From (21) and (22), the state estimation error dynamics can be rewritten as
\[
e_{k+1} = (\mathcal{T} A(h) - \mathcal{L}(h) C) e_k,
\]
(23)
where
\[
\mathcal{A}(h, \theta) = \sum_{i=1}^{N} h_i(\xi_k) \mathcal{A}_i(\theta),
\]
(24)
\[
\mathcal{A}_i(\theta) = A_i + \sum_{l=1}^{n_x} \sum_{j=1}^{n_x} \sigma_{n_x}(l) \sigma_{n_y}(j) \theta_{ij} G_i.
\]
We are now ready to formulate the UIO design problem.

Problem 2. Consider the TS fuzzy system (12). Determine matrices of appropriate dimensions \( \mathcal{T}, \mathcal{N} \) and \( \mathcal{L}(h) \) of the TS fuzzy UI observer (16) such that both the state estimate \( \hat{x}_k \) and the UI estimate \( \hat{d}_k \) asymptotically converge to the state \( x_k \) and the UI \( d_k \), respectively.

The following technical lemmas are useful for the design of TS fuzzy UI observers.

Lemma 2 [(42)]. Given matrices of appropriate dimensions \( A \) and \( B \). There exists a matrix \( \mathcal{X} \) such that \( \mathcal{X} A = B \) if and only if \( \mathcal{X} A^\dagger A = B \). Moreover, the general solution to \( \mathcal{X} A = B \) is given by
\[
\mathcal{X} = B A^\dagger + \mathcal{Y}(I - A A^\dagger),
\]
where \( \mathcal{Y} \) is an arbitrary matrix of appropriate dimension.

Lemma 3 [(43)]. Consider the MF-dependent inequality
\[
\mathcal{T}_{hh_{h+}} = \sum_{i=1}^{N} \sum_{j=1}^{N} h_i(\xi_k) h_j(\xi_k) h_i(\xi_{k+1}) \mathcal{T}_{ijl} \succ 0,
\]
(25)
where \( h_+ = [h_1(\xi_{k+1}), h_2(\xi_{k+1}), \ldots, h_N(\xi_{k+1})]^T \), and \( \mathcal{T}_{ijl} \in \mathcal{H} \). The symmetric matrices of appropriate dimensions \( \mathcal{T}_{ijl} \), with \( i, j, l \in I_n \), are linearly dependent on the unknown decision variables. Inequality (25) holds if
\[
\frac{2}{N - 1} \mathcal{T}_{iil} + \mathcal{T}_{ijl} + \mathcal{T}_{jil} \succ 0, \quad i, j, l \in I_n, \quad i \neq j.
\]
(26)
Note that Lemma 3 allows to convert the infinite LMI-based condition (25) into a finite set of LMI constraints (26), which is numerically tractable.
B. LMI-Based Unknown Input Observer Design

The following theorem provides a numerical tractable solution for the UIO design in Problem 2.

**Theorem 1.** Consider the TS fuzzy system (12), there is an asymptotic UI observer in the form (16) if there exist matrices $\mathcal{T}$ and $\mathcal{N}$ satisfying conditions (17) and (20), and if there exist positive definite matrices $P_i \in \mathbb{R}^{n_x \times n_x}$, matrices $M_i \in \mathbb{R}^{n_x \times n_x}$, for $i \in \mathcal{I}_N$, such that

$$\Phi_{iil}(\theta_p) > 0 \quad \text{(27a)}$$

$$\frac{2}{N-1} \Phi_{iil}(\theta_p) + \Phi_{ijl}(\theta_p) + \Phi_{jil}(\theta_p) > 0 \quad \text{(27b)}$$

for $i, j, l \in \mathcal{I}_N$, $i \neq j$, and $\theta_p \in \mathcal{V}_\phi$, $p \in \mathcal{I}_N$. The quantity $\Phi_{ijl}(\theta_p)$ is given by

$$\Phi_{ijl}(\theta_p) = \left[ P_j \mathcal{M} \mathcal{A} l_P(\theta_p) - L_j C \mathcal{M}_j + M_j^\top - P_1 \right],$$

with $\mathcal{A} l_P(\theta_p)$ defined in (24). Moreover, the matrix $L(h)$ in (16a) is defined as $L(h) = M^{-1}(h) L(h)$ with

$$M(h) = \sum_{i=1}^{N} h_i(\xi_k) \left[ M_i \quad L_i \right]. \quad \text{(28)}$$

**Proof.** Note that if matrices $\mathcal{T}$ and $\mathcal{N}$ satisfy conditions (17) and (20), then the TS fuzzy UI observer (16) leads to the state estimation error dynamics (23). Moreover, conditions (17) and (20) can be rewritten in the compact form

$$\begin{bmatrix} \mathcal{T} & \mathcal{N} \end{bmatrix} \begin{bmatrix} I & D \\ C & 0 \end{bmatrix} = \begin{bmatrix} I & 0 \end{bmatrix}. \quad \text{(29)}$$

Due to the rank condition (15b), the solution of the algebraic matrix equation (29) exists. Applying Lemma 2 with

$$A = \begin{bmatrix} I & D \\ C & 0 \end{bmatrix}, \quad B = \begin{bmatrix} I \\ 0 \end{bmatrix}, \quad \mathcal{X} = \left[ \mathcal{T} \quad \mathcal{N} \right],$$

we can compute matrices $\mathcal{T}$ and $\mathcal{N}$ as

$$\mathcal{X} = \left[ \begin{bmatrix} I & D \\ C & 0 \end{bmatrix} \right] \quad \text{and} \quad \mathcal{Y} \begin{bmatrix} I & D \\ C & 0 \end{bmatrix} = \begin{bmatrix} I & D \end{bmatrix}, \quad \text{(30)}$$

where $\mathcal{Y}$ is an arbitrary matrix of appropriate dimension.

For stability analysis, we consider the following MF-dependent Lyapunov function candidate:

$$\mathcal{V}(e_k) = e_k^\top P(h) e_k, \quad P(h) = \sum_{i=1}^{N} h_i(\xi_k) P_i. \quad \text{(31)}$$

By Lemma 3, it follows from (27a) and (27b) that

$$\begin{bmatrix} P(h) \\ M(h) \mathcal{T} \mathcal{A} (h, \theta) - L(h) C \mathcal{M} (h, h_+) \end{bmatrix} > 0, \quad \text{(32)}$$

for $h, h_+ \in \mathcal{H}$, $\theta \in \mathcal{V}_\phi$, with

$$\mathcal{M} (h, h_+) = M(h) + M(h)^\top - P(h_+),$$

and $P(h_+) = \sum_{i=1}^{N} h_i(\xi_k+1) P_i$. Since $P(h_+) > 0$, condition (32) implies $M(h) + M(h)^\top > 0$. This guarantees the existence of $M(h)^{-1}$, thus the validity of the expression of $L(h)$.

Let us denote $A(h, \theta) = \mathcal{T} \mathcal{A} (h, \theta) - \mathcal{L}(h) C = \mathcal{T} \mathcal{A} (h, \theta) - M(h)^{-1} L(h) C$. Premultiplying (32) with $[I - A(h, \theta)^\top]$ on the left and its transpose on the right, we obtain

$$A(h, \theta)^\top P(h_+) A(h, \theta) - P(h) < 0. \quad \text{(33)}$$

Note that inequality (33) guarantees a negative variation of the fuzzy Lyapunov function (31) along the trajectory of the error dynamics (23), i.e.,

$$\delta \mathcal{V}_k = \mathcal{V}(e_{k+1}) - \mathcal{V}(e_k) = e_{k+1}^\top P(h_{k+1}) e_{k+1} - e_k^\top P(h) e_k < 0, \quad \forall k \in \mathbb{Z}_+. \quad \text{(34)}$$

Using Lyapunov-based argument, it is clear that condition (34) guarantees the asymptotic stability of the error dynamics (23).

Hereafter, we show that the estimate $\hat{d}_k$ defined in (16c) converges asymptotically to the of the unknown input $d_k$. To this end, note from (12) that

$$d_k = (CD)^\top (y_{k+1} - C \Phi_k), \quad \text{(35)}$$

with $\Phi_k = A(h) x_k + f(x_k, u_k) + G(h) \phi(x_k, u_k)$. The UI estimation error $\varepsilon_k = \hat{d}_k - d_k$ can be computed from (16c) and (35) as

$$\varepsilon_k = (CD)^\top C (A(h) e_k + G(h) \delta_\phi). \quad \text{(36)}$$

Exploiting again expression (22), the UI estimation error $\varepsilon_k$ in (36) can be rewritten in the form

$$\varepsilon_k = (CD)^\top C \mathcal{A} (h, \theta) e_k. \quad \text{(37)}$$

Since $h$ and $\theta$ belong to bounded convex sets, i.e., $h \in \mathcal{H}$ and $\theta \in \mathcal{V}_\phi$, remark from the algebraic equation (37) that if $e_k \to 0$, then $\varepsilon_k \to 0$. This concludes the proof. \hfill \square

**Remark 3.** The observer design in Theorem 1 is recast as a convex optimization problem under strict LMI constraints (27). Hence, the decision matrices $M_i, L_i$, for $i \in \mathcal{I}_N$, constituting the observer gain $L(h)$ as in (28), can be efficiently solved with available numerical toolboxes, for instance YALMIP package with SDPT3 solver [44].

The UI observer design is summarized in Algorithm 1. The proposed UI observer design can be now applied to the TS fuzzy model (10) for the estimation of vehicle nonlinear dynamics as described in Problem 1.

**Algorithm 1: Observer Design Procedure**

**Input:** Nonlinear system in the TS fuzzy form (12)
**Output:** Unknown input observer (16) such that $\hat{x}_k \to x_k$ and $\hat{d}_k \to d_k$, when $k \to \infty$

1. Check the matrix rank conditions in Assumption 2
   - If YES, then go to Step 2
   - If NO, then unapplicable algorithm
2. Compute matrices $\mathcal{T}$ and $\mathcal{N}$ from (30)
3. Solve LMI conditions (27) to get $M_i, L_i$, for $i \in \mathcal{I}_N$
4. Construct matrices $M(h)$ and $L(h)$ from (28)
5. Construct TS fuzzy unknown input observer (16)
IV. HARDWARE-IN-THE-LOOP EXPERIMENTS

This section presents real-time results obtained with HiL experiments to demonstrate the effectiveness of the proposed fuzzy UI observer design. Three test scenarios, representing different normal driving situations, are performed on a high-fidelity vehicle model to show the robustness of the new observer with respect to unmodeled vehicle dynamics.

A. Hardware-in-the-Loop Simulation Platform Setup

1) Full Vehicle Model: The real-time verification of the proposed nonlinear UI observer is performed with a 15-DOF multibody vehicle model [45], developed in LMS Imagine.Lab AMESim environment. This full vehicle model consists of a powertrain-chassis subsystem, a tire-road subsystem, a vehicle dynamics sensing subsystem and a vehicle control unit as depicted in Fig. 2. The key vehicle parameters are given in Table I while others are initialized by AMESim [45] to create a challenging simulation environment. The vehicle control unit is constructed in Simulink and embedded in AMESim via a co-simulation interface. Without further precision on the test scenarios, it is assumed that the vehicle drives on a flat ground with an ideal or a time-varying road adherence.

![Fig. 2. AMESim full vehicle model running on HiL platform.](image)

2) Hardware-in-the-Loop Platform Setup: To evaluate the practical estimation performance, a HiL platform has been setup as shown in Fig. 3(a). This platform consists of two real-time (RT) machines: a MicroAutoboxII (MABII) and a Vector System (VTS), and a personal computer to monitor and download programmes into the RT machines via their application tools: ControlDesk and CANoe/Pro. For the RT code generation, the MABII has been selected as the platform to run the full vehicle model while the VTS has been selected as the platform to function as the vehicle sensing system as well as to implement the designed fuzzy UI observer. All the programs have been implemented in Simulink, allowing RT code generation with RT interfaces from the dSPACE and the VTS, see Figs. 3(b) and (c), respectively. At each operation step, to mimic the practical automotive application, pulse-width modulation (PWM) output channels of the MABII are used to send the virtual sensor signals from the AMESim full vehicle model to the VTS. The VTS receives the MABII signals via its PWM input channels and converts them to physical signals.

![Fig. 3. Hardware-in-the-loop platform setup.](image)

B. Scenario 1: Driving with a Random Vehicle Trajectory

For this test scenario, the autonomous vehicle performs a driving task with a random trajectory and an increased acceleration after 14 [s] as shown in Figs. 4(a) and (b). Observe from Figs. 4(b), (c) and (d) that the estimated vehicle states quickly converge to their measured values. Moreover, Fig. 5 shows that both the unknown steering angle and the effective engine torque are accurately estimated with the proposed TS fuzzy observer.

![Fig. 4. Scenario 1: Driving with a Random Vehicle Trajectory.](image)
Fig. 4. Estimation performance in Scenario 1. (a) Vehicle trajectory. (b) Longitudinal speed $v_x$. (c) Lateral speed $v_y$. (d) Yaw rate $r$.

Fig. 5. Estimation performance in Scenario 1. (a) Steering angle $\delta$. (b) Effective engine torque $T_{\text{eng}}$.

C. Scenario 2: Driving with a Circular Vehicle Trajectory

For this driving scenario, the estimation performance is tested with a circular trajectory as depicted in Fig. 6(a). The corresponding vehicle speed is given in Fig. 6(b). We can see that the unmeasured lateral speed and unknown vehicle inputs can be accurately reconstructed with the proposed fuzzy UI observer as shown in Fig. 6(c) and Fig. 7, respectively. Moreover, as in the previous driving scenario, the estimation convergence is very quick for all estimated vehicle variables.

Fig. 6. Estimation performance in Scenario 2. (a) Vehicle trajectory. (b) Longitudinal speed $v_x$. (c) Lateral speed $v_y$. (d) Yaw rate $r$.

Fig. 7. Estimation performance in Scenario 2. (a) Steering angle $\delta$. (b) Effective engine torque $T_{\text{eng}}$.

D. Scenario 3: Driving with a Time-Varying Road Adherence

This test is performed with a time-varying adherence condition to emphasize the robustness performance of the proposed UI observer. For this scenario, we assume that the autonomous vehicle performs a contour trajectory with radius varied from 45 [m] to 55 [m] and an increasing vehicle speed profile as shown in Figs. 8(a) and (b), respectively. To design a challenging driving situation, the interaction between the ground and the tires is now simulated by a road grip model as shown in Fig. 2, which is driven by the vehicle movement as

$$\text{Road}_{\text{grip}} = \mu_{\text{grip}} \left(1 + \sin \left(\frac{\pi \sqrt{X^2 + Y^2}}{l_r}\right)\right),$$

where $\mu_{\text{grip}} = 0.6$ is the grip coefficient, $X$ and $Y$ are the vehicle positions. We can observe in Fig. 8 that the estimation of the vehicle states is also highly accurate in this situation. In particular, the proposed UI observer allows capturing precisely the high-frequency chattering behaviors of vehicle variables related to the lateral motion. The estimates of the steering angle and the effective engine torque also converges quickly to their respective measured signals as depicted in Fig. 9.

Fig. 8. Estimation performance in Scenario 3. (a) Vehicle trajectory. (b) Longitudinal speed $v_x$. (c) Lateral speed $v_y$. (d) Yaw rate $r$.

For a quantitative performance analysis, the mean absolute errors (respectively root mean square deviations) of the unmeasured lateral speed $v_y_{\text{MAE}}$, steering angle $\delta_{\text{MAE}}$ and effective engine torque $T_{\text{eng}}_{\text{MAE}}$ (respectively $v_y_{\text{RMSD}}$, $\delta_{\text{RMSD}}$ and $T_{\text{eng}}_{\text{RMSD}}$) obtained with the proposed UI observer are computed. These performance indices are summarized in Table II for the three driving scenarios. The analysis results confirm that the proposed fuzzy UI observer can provide accurate
estimates of both vehicle state variables and unknown inputs under all considered test scenarios.

### TABLE II

<table>
<thead>
<tr>
<th>Error index</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_{MAE}$ [rad]</td>
<td>0.0018</td>
<td>9.71e-5</td>
<td>0.0023</td>
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<tr>
<td>$T_{engMAE}$ [Nm]</td>
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<td>0.7329</td>
<td>0.7553</td>
</tr>
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<td>$v_{yRMSD}$ [m/s]</td>
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<td>2.19e-4</td>
<td>2.96e-6</td>
</tr>
<tr>
<td>$\delta_{RMSD}$ [rad]</td>
<td>2.53e-4</td>
<td>2.91e-6</td>
<td>2.14e-4</td>
</tr>
<tr>
<td>$T_{engRMSD}$ [Nm]</td>
<td>5.164</td>
<td>5.212</td>
<td>5.319</td>
</tr>
</tbody>
</table>

### V. CONCLUDING REMARKS

A new nonlinear UI observer design method has been proposed to simultaneously estimate the vehicle state, the lateral speed as well as the effective engine torque of autonomous ground vehicles. TS fuzzy modeling with nonlinear consequents is exploited for observer design to deal with the unmeasured nonlinearities of the combined longitudinal-lateral vehicle dynamics. The proposed generalized Luenberger observer structure permits an effective UI decoupling to guarantee an asymptotic convergence of both the vehicle state and the UI estimation errors. LMI-based observer design conditions are derived using Lyapunov arguments. The practical performance of the new fuzzy UI observer is real-time tested with a high-fidelity AMESim vehicle model. The results of HiL experiments show that the proposed nonlinear UI observer can provide accurate estimates of both vehicle state variables and UIs. Future works focus on the extension of the proposed estimation method to deal with limit driving situations, e.g., by taking into account a nonlinear tire model or parametric uncertainties of the cornering stiffness parameters in the observer design. Moreover, exploiting the proposed UI observer structure for an effective fault-tolerant control scheme of autonomous vehicles is another promising research topic.

### REFERENCES


Fig. 9. Estimation performance in Scenario 3. (a) Steering angle $\delta$. (b) Effective engine torque $T_{eng}$. 


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