Lateral Wind Estimation and Backstepping Compensation for Safer Self-Driving Racecars

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***Abstract*— This paper addresses the lateral wind gust estimation and compensation problem for racecar models. A wind-sensorless solution, i.e. a solution not using direct wind measures, is proposed. More precisely, by modeling the wind disturbance as a fully unknown input signal, an input-state observer is derived using only information about the vehicle's longitudinal speed and lateral pose relative to the road. The observer is characterized by a simple structure, explicit closed-form, direct implementability on a micro-controller, and dead-beat property, i.e. it ensures the convergence of the estimation error in a finite time. Moreover, leveraging on the reconstructed wind data, a backstepping wind-compensation controller is also proposed, allowing asymptotic tracking of a path with desired curvature and providing the end-user with a free control parameter specifying the desired tracking speed. Formal proofs of the estimation error and tracking error convergence are given. Performance evaluation of the proposed solution is obtained in simulation by closing in the loop the full nonlinear model of a real racecar, the Robocar system, with the proposed estimation and control method. Both the estimator and the controller are shown to outperform existing solutions, even in the presence of noisy measurements.**

***Index Terms*— Autonomous vehicles, estimation, wind compensation, racecars.**

I. Introduction

ROAD accidents cause fatalities and injuries. These accidents have an impact on the cost of insurance, which is passed on to the drivers, to compensate for the loss of life, pain, and suffering, healthcare for the longer-term injuries, and damage to the vehicles. Every year, nearly 1.3 million people worldwide lose their life on roads, and 20-50 million sustain severe injuries [1]. Many national and international authorities are now pushing local governments to adopt strategic action plans towards road safety, in order to drastically reduce the road fatality numbers between the years 2020 and 2030 [2]. A major contributing cause of road accidents is the presence of sudden wind gusts [3], especially when accompanied by other adverse weather conditions [4] or poor asphalt state [5], which directly impacts the severeness of the hazard, as they affect the vehicle's road-holding capacity. For example, it is estimated that, in California, the death percentage in wind-related accidents is more than twice that of all other weather-related ones [6]. Moreover, with reference to a vehicle's motion, longitudinal wind gusts roughly impact the system performance and traveling fuel consumption only. In contrast, lateral ones can impair the vehicle's safety by blowing it off the road, into another vehicle, or even tipping it over [7].

In a continuous effort to improve performance and safety, and hence also to reduce possible road accidents, the automotive industry has paid attention, during the last two decades, to ways for ameliorating existing traction control systems and electronic stability control, and providing new Advanced Driver-Assistance Systems (ADAS) technology such as brake assist, lane keeping [8], and adaptive cruise control [9], [10], [11]. In the meanwhile, the scientific community has envisioned a further step towards safety with novel self-driving and cooperative frameworks, whose implementation leverages road condition observers [12], [13], proactive collision detection [14], spacing policies for planning and control of vehicle platoons [15], [16], and automated pilots capable of identifying current maneuvers performed by a human driver or to predict future ones [17], [18], to avoid any possible collision. An important maturity level of these solutions has already been proven by pilot projects, such as SARTRE [19] and COMPANION [20] and during the Roborace challenge [21], involving self-driving electric racecars, so-called Robocars. However, before contributing to a concrete reduction of road accidents, self-driving technologies need better perception and reaction capacities to the complexity of a real traveling experience, including the handling of disturbance signals due to wind gusts that are considered here.

Roughly speaking, the lateral dynamics control problem in the presence of wind amounts to deciding the correct value of the vehicle steering angle, which is the system control input, that is needed to compensate for the wind effects and to track the desired path. Intuitively, the absolute amplitude of such an angle increases with the ratio between the wind force and the vehicle mass, as well as that between the wind moment and its inertia. At the same time, it decreases with an increase in the vehicle's longitudinal speed. Having an accurate estimate of the wind force and moment and precisely determining the steering angle command as feedback of the system state is essential to avoid overcompensation or under-

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compensation, which would result in undesirable overshooting or slow behavior of the system response.

In this respect, to retrieve high-accuracy wind information, wind measurement solutions available now involve special anemometer sensors, consisting of a five-hole probe [22], which were originally developed for aviation applications. They provide wind speed and direction data, once the speed and orientation of the vehicle on which they are installed are known. So far used only in racecars [23] and trains [24], they have the disadvantage of requiring a calibration based on the air density at the local altitude and placement not too close to the car surface to capture only laminar flow measurement. Only very recently [25], the promising usage of Light Detection And Ranging (LIDAR) sensors has been proposed to obtain wind speed information, which still introduces a substantial cost to the vehicle. However, determining the actual force acting on the vehicle, from knowledge of the wind speed, involves precise knowledge of vehicle-dependent aerodynamic coefficients. It would be advantageous instead to be able to estimate the wind force and moment directly from data already available on present vehicles, such as GPS and onboard encoders. Moreover, even when the wind force and moment data are available, effective lateral wind compensation control schemes actively using them are missing as of today and should be developed.

Within this context, the present paper focuses on wind-sensorless estimation and compensation for racecar models affected by lateral wind gusts. More precisely, for the estimation objective, after conveniently reformulating the nonlinear lateral model of a racecar in a form where suitable combinations of the unknown lateral wind force and moment signals act as unknown inputs, a linear input-state observer is built upon Unknown Input Observer (UIO) theory [26]. The observer uses measures of the current lateral vehicle pose, obtained e.g. via a GPS sensor, and reconstructs the full system state and unknown inputs, which is enabled by the strong observability and the system invertibility properties of the attained model when using such an output. It is worth noticing that, through this choice, our method does not use costly and robust wind sensors, yet it relies on easily accessible GPS sensors. In this respect, the framework of so-called "delayed" discrete-time UIOs has been chosen, among the others available (see e.g. [27], [28], [29], [30]), for their advantage of involving looser existence conditions and achieving estimators with a simpler structure, explicit closed-form, direct implementability on a micro-controller, and dead-beat design, i.e. they ensure that the estimation error vanishes in a finite time, at the only expense of collecting output samples for a very small interval. Moreover, the well-known Extended Kalman Filters can be used [31], but however, they would require tuning a set of parameters that depend on the specific noise signals and still do not guarantee the convergence to zero of the estimation error. Moreover, as for the subsequent objective of compensating for the wind effect, a novel backstepping controller is proposed whose convergence is formally proved. The robustness of the proposed UIO-based controller is tested in simulation with the model of real Robocar system [21] against the occurrence of wind gusts modeled by the well-known Dryden model [32].

A. Contribution

The contributions of this paper are at least threefold. First, a state and wind estimator is designed which uses no direct measures of the wind force and moment affecting the lateral dynamics of a racecar. The estimator uses only longitudinal speed and lateral pose (position and orientation) error measurement of the vehicle that is available e.g. via a GPS sensor. Compared to solutions obtained by using the well-known Extended Kalman Filters [31], the proposed estimator has a simpler mathematical structure, requires no parameter tuning, possesses convergence guarantees, and, above all, is much faster. Secondly, the herein proposed backstepping wind-compensation controller uses only longitudinal speed, car pose, and estimated wind information and provides the end-user with a free control parameter specifying the desired convergence speed for the lateral pose error. Without using lateral pose speed, it outperforms existing PI regulators [33] and other backstepping solutions [34], thanks to its ability to anticipate the compensation action, even when the car is performing aggressive maneuvers. Thirdly, the paper reports simulation performance results when the overall estimation and compensation solution is closed in the loop with a fully nonlinear model of a racecar [21], simulated by using the Vehicle Dynamics Blockset [35].

The paper is organized as follows. Sec. II presents the lateral dynamic model of a racecar and the problem statement, and it recalls the background on delayed input-state observers. Sec. III describes the first main result of the work, which consists of a wind force and moment estimator based on a convenient reformulation of the racecar model. The subsequent Sec. IV derives and proposes a backstepping-based controller, that uses the information reconstructed by the estimator. Sec. V presents the validation of the proposed approach through the implementation in Matlab/Simulink of a wind-influenced realistic scenario, where a complete Robocar system is required to execute aggressive maneuvers where both the longitudinal speed and the yaw rate of the desired path are changing simultaneously. The section also shows the comparison of the system, closed in the loop with the proposed UIO or the EKF, as well as the proposed backstepping controller or other existing ones.

II. Problem Statement and Related Work

A. System Model and Problem Statement

Consider a racecar with front steering and rear traction that is traveling along a flat horizontal road. Referring to Fig. 1, let (X, Y) be the coordinates of the center of mass G of the vehicle in an Inertial frame, and (x, y) those in a body frame attached to the vehicle; let also ψ be the heading direction of the vehicle with respect to the X-axis. Given a path to be tracked, let (X_d, Y_d) be the desired position and ψ_d the desired orientation, measured from the X-axis. Moreover, assuming that a GPS sensor is used to instantaneously measure X, Y, and ψ, a lateral position error variable can be introduced as the projection of the error vector $(X, Y)^T - (X_d, Y_d)^T$ along the lateral direction unit vector $(-\sin\psi, \cos\psi)^T$, i.e. $e_1 = (Y - Y_d)\cos\psi - (X - X_d)\sin\psi$; finally an orientation error can be introduced as $e_2 = \psi - \psi_d$. Assuming the absence of

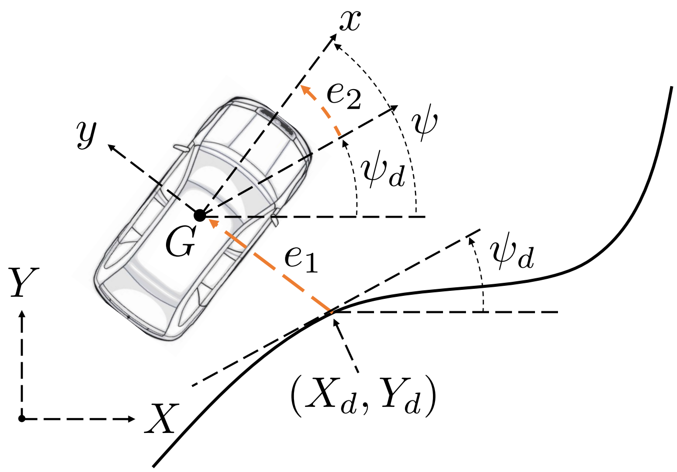

Fig. 1. Illustration of the vehicle schematic, desired path, and coordinate frames.

TABLE I
NOMINAL INERTIAL AND GEOMETRIC PARAMETERS OF A ROBOCAR FROM THE ROBORACE CHALLENGE [21]

Parameters	Value	Unit
Front cornering stiffness, γ_1	226	[kN,/ rad]
Rear cornering stiffness, γ_2	282	[kN / rad]
Car's moment of inertia, J	1150	[kg·m^2]
Front wheelbase, a_1	1.51	[m]
Rear wheelbase, a_2	1.288	[m]
Mass, m	1350	[kg]

pitching and rolling motions, the vehicle's lateral dynamics is described by the so-called single-track model [36] which has the state-form [37]:

$$\dot{Z} = A_c(u)\, Z + B_\delta\, \delta + B_{c,r}(u)\, r_d + B_w\, F\,, \tag{1}$$

where $Z = (e_1, \dot{e}_1, e_2, \dot{e}_2)^T$, δ is the wheel's steering angle and the system's control input, u is the vehicle's longitudinal speed, $r_d = \dot{\psi}_d$ is the desired yaw rate, $F = (F_w, \tau_w)^T$ is the vector of the lateral wind force and moment,

$$A_c(u) = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & -\frac{\gamma_s}{mu} & \frac{\gamma_s}{m} & \frac{\gamma_m}{mu} \\ 0 & 0 & 0 & 1 \\ 0 & \frac{\gamma_p}{Ju} & -\frac{\gamma_m}{J} & -\frac{\gamma_q}{Ju} \end{pmatrix},\ B_\delta = \begin{pmatrix} 0 \\ \frac{\gamma_1}{m} \\ 0 \\ \frac{\gamma_1 a_1}{J} \end{pmatrix},$$
$$B_{c,r} = \begin{pmatrix} 0 \\ \frac{\gamma_m}{mu} - u \\ 0 \\ -\frac{\gamma_q}{Ju} \end{pmatrix},\ B_w = \begin{pmatrix} 0 & 0 \\ \frac{1}{m} & 0 \\ 0 & 0 \\ 0 & \frac{1}{J} \end{pmatrix}, \tag{2}$$

with $\gamma_s = \gamma_1 + \gamma_2$, $\gamma_p = \gamma_1 a_1 + \gamma_2 a_2$, $\gamma_m = \gamma_2 a_2 - \gamma_1 a_1$, and $\gamma_q = \gamma_1 a_1^2 + \gamma_2 a_2^2$, and all other geometric and inertial parameters are as in Table I. Despite its simplicity, the model is known to be well suited to describe the system behavior, under the hypothesis that the vehicle moves with small steering angles, which is always the car with racecars [36]. Moreover, assuming the lateral error pose can be measured via GPS sensors, one can define the following output map:

$$Y = C\, Z + D_\delta\, \delta + D_r\, r_d + D_w\, F\,, \tag{3}$$

with

$$C = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix},\ \begin{matrix} D_\delta = D_r = 0_{2\times 1}, \\ D_w = 0_{2\times 2}. \end{matrix} \tag{4}$$

Within this context, this paper aims at seeking solutions for the following problems:

Problem 1: Find an estimator that allows reconstructing sudden wind gust signals, without using direct wind measures, acting on a racecar system described by the model in (1) and (3).

Problem 2: Given the desired path with a yaw rate r_d and wind force and moment estimates obtained from a wind estimator, design a feedback controller for the steering angle δ, ensuring the asymptotic convergence of the lateral error e_1.

B. Delayed Unknown Input Observers

This section recalls some useful results from [26] upon which our proposed estimation solution is built. Consider a discrete-time linear system described by the state form

$$Z_{k+1} = A\, Z_k + B\, U_k, \quad Y_k = C\, Z_k + D\, U_k\,, \tag{5}$$

where $Z_k \in \mathbb{R}^n$ is the state vector, $U_k \in \mathbb{R}^m$ is an unknown input vector, $Y_k \in \mathbb{R}^p$ is the output vector. For a non-negative integer L, the L-step input and output histories are the vectors $\mathbb{U}_k^L = (U_k, \cdots, U_{k+L})$ and $\mathbb{Y}_k^L = (Y_k, \cdots, Y_{k+L})$, respectively. They are related via the expression $\mathbb{Y}_k^L = \mathbb{O}^L Z_k + \mathbb{H}^L \mathbb{U}_k^L$, where $\mathbb{O}^L$ and $\mathbb{H}^L$ are the L-step observability and invertibility matrices, respectively, which are defined as

$$\mathbb{O}^L = \begin{pmatrix} C \\ \mathbb{O}^{L-1} A \end{pmatrix},\quad \mathbb{H}^L = \begin{pmatrix} D & 0 \\ \mathbb{O}^{L-1} B & \mathbb{H}^{L-1} \end{pmatrix},\ \text{for } L \geq 1\,,$$

and $\mathbb{O}^0 = C$ and $\mathbb{H}^0 = D$. Then, the following definition can be given:

Definition 1 (Delayed Unknown Input Observer, UIO): A discrete-time linear system of the form

$$\hat{Z}_{k+1} = E\, \hat{Z}_k + \Phi\, \mathbb{Y}_k^L\,, \quad \hat{U}_k = G \begin{pmatrix} \hat{Z}_{k+1} - A\, \hat{Z}_k \\ Y_k - C\, \hat{Z}_k \end{pmatrix}, \tag{6}$$

where E, Φ, and G are suitable matrices, is a UIO, with delay L, for the dynamic system in (5), if, for all $\hat{Z}_0$ and Z_0, it ensures that $\hat{Z}_k \to Z_k$, as $k \to \infty$, for every input signal U_k. □

Having defined the state estimation error as $e_k = \hat{Z}_k - Z_k$, a UIO of the form in (6) must satisfy the conditions:

A1) $\Phi\, \mathbb{H}^L = (B, 0_{n\times m})$ (*input decoupling*);
A2) $E = A - \Phi\, \mathbb{O}^L$ (*state decoupling*);
A3) E is Schur, i.e. all its eigenvalues are within the unit circle (*error convergence*).

Given the sequence of invertibility matrices, $\mathbb{H}^L$, for $L = 1, \cdots, n$, the solvability of Condition A1 is related to the following property:

Proposition 1 (System Invertibility): The model in (5) is *invertible* with delay L, if, and only if,

$$\text{rank}(\mathbb{H}^L) = m + \text{rank}(\mathbb{H}^{L-1})\,.$$

If the above property is satisfied and $(B^T, D^T)^T$ is full column rank, a matrix G allowing the reconstruction of the unknown input U_k is such that

$$G \begin{pmatrix} B \\ D \end{pmatrix} = \mathbb{I}_m \,, \tag{7}$$

where $\mathbb{I}_m$ is the identify matrix of order m. Finally, Conditions A2) and A3) can be solved if, and only if, the model in (5) is *strongly observable* with delay L, i.e. if, for any initial state Z_0 and any unknown input sequence $\{U_k\}$, there exists $L \geq 1$ such that Z_0 can be recovered from the output sequence $\{Y_k\}$. Given also the sequence of observability matrices, $\mathbb{O}^L$, for $L = 1, \cdots, n$, the above property is stated in the following:

Proposition 2 (Strong Observability): The model in (5) is *strongly observable* with delay L if, and only if,

$$\operatorname{rank}([\mathbb{O}^L, \mathbb{H}^L]) = n + \operatorname{rank}(\mathbb{H}^L) \,.$$

III. Design of the Lateral Wind Estimator

To derive the sought input-state observer, the continuous-time racecar model in (1) needs to be discretized with respect to time by using a first-order Euler approximation of the involved time derivatives. This yields the following discrete-time model:

$$\begin{aligned} Z_{k+1} &= \tilde{A}(u_k)\, Z_k + \tilde{B}(u_k)\, \tilde{U}_k \,, \\ Y_k &= C\, \tilde{Z}_k + \tilde{D}\, \tilde{U}_k \,, \end{aligned} \tag{8}$$

where the state vector is $Z_k = (e_{1,k}, \dot{e}_{1,k}, e_{2,k}, \dot{e}_{2,k})^T$, the input vector is $\tilde{U}_k = (\delta_k, r_{d,k}, F_{w,k}, \tau_{w,k})^T$, the output vector is $Y_k = (e_{1,k}, e_{2,k})^T$ and it is measurable through a GPS sensor, and the matrices are:

$$\tilde{A} = I + T_s A_c(u_k) = \begin{pmatrix} 1 & T_s & 0 & 0 \\ 0 & 1 - \frac{\gamma_s T_s}{m u_k} & \frac{\gamma_s T_s}{m} & \frac{\gamma_m T_s}{m u_k} \\ 0 & 0 & 1 & T_s \\ 0 & \frac{\gamma_m T_s}{J u_k} & -\frac{\gamma_m T_s}{J} & 1 - \frac{\gamma_q T_s}{J u_k} \end{pmatrix},$$

$$\tilde{B} = T_s \left(B_\delta, B_{c,r}, B_w\right) = \begin{pmatrix} 0 & 0 & 0 & 0 \\ \frac{\gamma_1 T_s}{m} & \left(\frac{\gamma_m}{m u_k} - u_k\right) T_s & \frac{T_s}{m} & 0 \\ 0 & 0 & 0 & \\ \frac{\gamma_1 a_1 T_s}{J} & -\frac{\gamma_q T_s}{J u_k} & 0 & \frac{T_s}{J} \end{pmatrix},$$

where A_c, $B_{c,r}$ and the other control vectors are defined in (2), and finally $\tilde{D} = (D_\delta, D_{c,r}, D_w)$, that is $D = 0_{2\times 4}$.

We are now ready to obtain the first main result of this paper, which solves Prob. 1 and is stated in the following:

Theorem 1: Given a racecar with lateral dynamics as in (1) and a sampling time T_s, a delayed. UIO reconstructing the wind disturbance vector F is described by the iterative system:

$$\begin{aligned} \hat{Z}_{k+1} &= E\, \hat{Z}_k + \Phi\, \mathbb{Y}_k \,, \\ \hat{U}_k &= \begin{pmatrix} \hat{U}_{1,k} \\ \hat{U}_{2,k} \end{pmatrix} = G \begin{pmatrix} \hat{Z}_{k+1} - A\, \hat{Z}_k \\ Y_k - C\, \hat{Z}_k \end{pmatrix}, \end{aligned} \tag{9}$$

where k is a discrete step time, the state vector and the output history are $\hat{Z}_k = (\hat{e}_{1,k}, \hat{\dot{e}}_{1,k}, \hat{e}_{2,k}, \hat{\dot{e}}_{2,k})^T$ and $\mathbb{Y}_k = (Y_{k-2}, Y_{k-1}, Y_k)^T$, respectively, the C is as in (4) and the other matrices are

$$E = \begin{pmatrix} 1 & T_s & 0 & 0 \\ -\frac{1}{T_s} & -1 & 0 & 0 \\ 0 & 0 & 1 & T_s \\ 0 & 0 & -\frac{1}{T_s} & -1 \end{pmatrix},$$

$$\Phi = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{T_s} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{T_s} \end{pmatrix},$$

$$G = \begin{pmatrix} 0 & \frac{1}{T_s} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{T_s} & 0 & 0 \end{pmatrix},$$

$$A = \begin{pmatrix} 1 & T_s & 0 & 0 \\ 0 & 1 & \frac{\gamma_s T_s}{m} & 0 \\ 0 & 0 & 1 & T_s \\ 0 & 0 & -\frac{\gamma_m T_s}{J} & 1 \end{pmatrix}. \tag{10}$$

Finally, the best-effort wind input vector estimate $\hat{F}_k = (\hat{F}_{w,k}, \hat{\tau}_{w,k})^T$ can be obtained by the formulas:

$$\begin{aligned} \hat{F}_{w,k} &= m\, \hat{U}_{1,k} + \frac{\gamma_s}{u_k}\, \hat{Z}_{2,k} - \frac{\gamma_m}{u_k}\, \hat{Z}_{4,k} + \\ &\quad - \gamma_1\, \delta_k + \left(m\, u_k - \frac{\gamma_m}{u_k}\right) r_{d,k} \,, \\ \hat{\tau}_{w,k} &= J\, \hat{U}_{2,k} - \frac{\gamma_m}{u_k}\, \hat{Z}_{2,k} + \frac{\gamma_q}{u_k}\, \hat{Z}_{4,k} + \\ &\quad - \gamma_1 a_1\, \delta_k + \frac{\gamma_q}{u_k}\, r_{d,k} \,. \end{aligned} \tag{11}$$

Proof 1: (State Reconstruction) Let us start with the procedure to obtain an estimate of the current system's state Z_k. The theoretical results recalled in Sec. II-B require the system's dynamics to be linear and time-invariant. In our case, the model includes terms depending on the longitudinal vehicle's speed u_k, which is externally controlled, and the desired yaw rate r_d, which is specified at a higher level based on required changes in the vehicle's direction. These two variables can be assumed to be known yet time-varying, thereby leading to time-varying matrices $\tilde{A}(u_k)$ and $\tilde{B}(u_k)$. The strategy that can be adopted here is that of collecting all time-varying or nonlinear quantities into a product $B\, U_k$, where B and U_k are a suitable control matrix and an input vector as in (5). Indeed, the quantity $B\, U_k$ can model nonlinearities, parametric uncertainties, etc [38]. To obtain this, one can first observe that matrix $\tilde{A}$ can be additively separated as

$$\tilde{A} = A + \begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & -\frac{\gamma_s T_s}{m u_k} & 0 & \frac{\gamma_m T_s}{m u_k} \\ 0 & 0 & 0 & 0 \\ 0 & \frac{\gamma_m T_s}{J u_k} & 0 & -\frac{\gamma_q T_s}{J u_k} \end{pmatrix} = A + A^*(u_k) \,,$$

where A is defined in (10). Then, one can impose the following identity:

$$A^*(u_k)\, Z_k + \tilde{B}(u_k)\, \tilde{U}_k = B\, U_k \,,$$

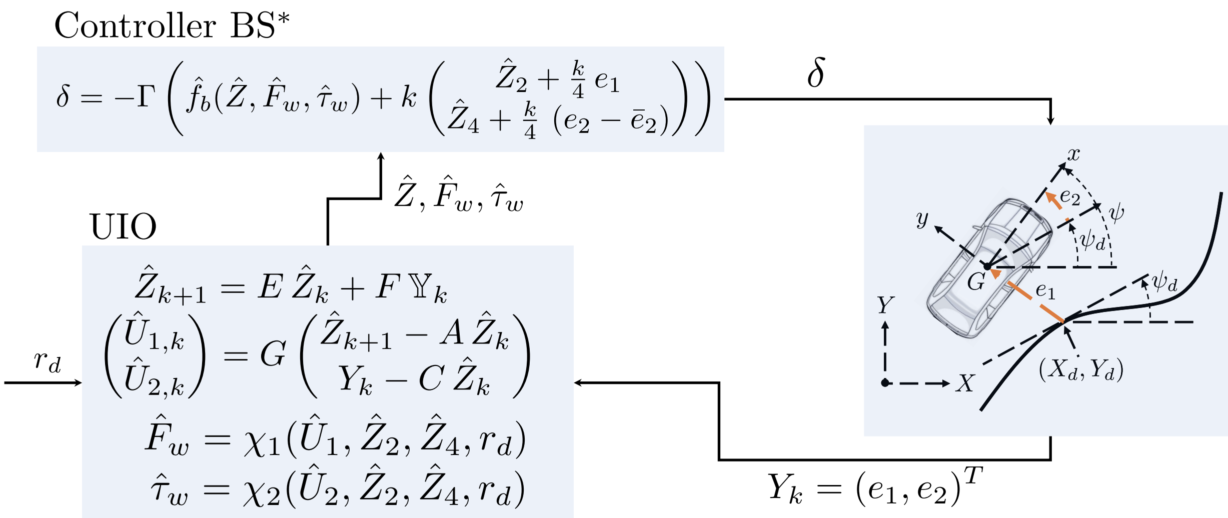

Fig. 2. Illustration of the racecar system closed in the loop with the proposed UIO-based estimator, and the proposed backstepping controller. Given a desired path, the desired coordinates on the curve describing such a path are (X_d, Y_d), while ψ_d and r_d are the desired orientation and yaw rate, respectively. The outputs of the racecar are the position and orientation errors, e_1 and e_2, and are used by the UIO-based estimator to reconstruct the current full system state Z and, along with the information about r_d, those of the wind force and moment. Once the estimates $\hat{Z}$, $\hat{F}_w$ and $\hat{\tau}_w$ are determined, the proposed backstepping controller determines the value of the input steering angle, ensuring the asymptotic convergence of the tracking errors.

which, thanks to the structure of A^* and the control matrix $\tilde{B}$, can be satisfied by the following choice:

$$B = \begin{pmatrix} 0 & 0 \\ T_s & 0 \\ 0 & 0 \\ 0 & T_s \end{pmatrix}, \quad U_k = \begin{pmatrix} U_{1,k} \\ U_{2,k} \end{pmatrix}, \tag{12}$$

with

$$\begin{aligned} U_{1,k} &= -\frac{\gamma_s}{m u_k}\,\dot{e}_1 + \frac{\gamma_m}{m u_k}\,\dot{e}_2 + \frac{\gamma_1}{m}\,\delta_k \\ &\quad + \left(\frac{\gamma_m}{m u_k} - u_k\right) r_{d,k} + \frac{1}{m}\,F_{w,k}\,, \\ U_{2,k} &= \frac{\gamma_m}{J u_k}\,\dot{e}_1 - \frac{\gamma_q}{J u_k}\,\dot{e}_2 + \frac{\gamma_1 a_1}{J}\,\delta_k + \\ &\quad - \frac{\gamma_q}{J u_k}\,r_{d,k} + \frac{1}{J}\,\tau_{w,k}\,. \end{aligned} \tag{13}$$

This leads us to a time-invariant linear system as in (5), where A is described in (10), B is in (12), C is in (4), and D is a null matrix of suitable dimensions. Direct calculation shows that the system model is strongly observable (Prop. 2) and invertible (Prop. 1) with a delay value of $L = 2$. Indeed, given the sequence

$$\mathbb{H}^1 = 0_{4\times 4}\,, \quad \mathbb{H}^2 = \begin{pmatrix} 0_{4\times 2} & 0_{4\times 4} \\ T_s^2\,\mathbb{I}_2 & 0_{2\times 4} \end{pmatrix},$$

it holds $\mathrm{rank}(\mathbb{H}^1) = 0$, $\mathrm{rank}(\mathbb{H}^2) = 2$ and hence $\mathrm{rank}(\mathbb{H}^2) - \mathrm{rank}(\mathbb{H}^1) = 2 = m$, where m is the dimension of our U_k, and then it also holds $\mathrm{rank}([\mathbb{O}^2, \mathbb{H}^2]) - \mathrm{rank}(\mathbb{H}^2) = 4 = n$, where n is the dimension of Z_k. Therefore, the derivation of the sought input-state observer can now be done as described below, by the reasoning described in [26]. The third condition A3) listed in the previous section, for $m = 2$ and $L = 2$, requires that matrix Φ satisfies the equation

$$\Phi\,\mathbb{H}^2 = (B, 0_{4\times 2})\,. \tag{14}$$

The above relation first implies that $\Phi \in \mathbb{R}^{4\times 6}$ must be in the left nullspace of the last $Lm = 4$ columns of $\mathbb{H}^2$. This condition is satisfied for every Φ since the last 4 columns of $\mathbb{H}^2$ are $\begin{pmatrix} 0 \\ \mathbb{H}^1 \end{pmatrix} = 0_{6\times 4}$. Furthermore, Eq. 14 also implies that

$$\Phi\begin{pmatrix} 0_{4\times 2} & 0_{4\times 4} \\ T_s^2\,\mathbb{I}_2 & 0_{2\times 4} \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ T_s & 0 \\ 0 & 0 \\ 0 & T_s \end{pmatrix}.$$

The simplest choice of Φ satisfying the above condition is the one reported in (10). Moreover, given the 2-step observability matrix

$$\mathbb{O}^2 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & T_s & 0 & 0 \\ 0 & 0 & 1 & T_s \\ 1 & 2\,T_s & \frac{\gamma_s T_s^2}{m} & 0 \\ 0 & 0 & 1 - \frac{\gamma_m T_s^2}{J} & 2\,T_s \end{pmatrix},$$

the second condition A2) yields the estimation error dynamic matrix E reported in (10). Direct verification shows that all eigenvalues of E are in the origin, which guarantees that the obtained estimator is asymptotically stable and has dead-beat property. Finally, since matrix $(B^T, D^T)^T$ is full column rank, it is possible to find a matrix G that satisfies (7), with $m = 2$, whose solution can be computed via the pseudo-inverse and gives the expression reported in (10).

(Input Reconstruction): By inverting (13) and substituting the state variables with the corresponding observer's variables, that is $\hat{\dot{e}}_1 = \hat{Z}_{2,k}$ and $\hat{\dot{e}}_2 = \hat{Z}_{4,k}$, one obtains the best-effort estimate of the unknown wind vector described in (11).

IV. Design of the Backstepping Controller With Wind Compensation

This subsection focuses on the design of a backstepping control law allowing the stabilization of the system model, with compensation of the effect of the estimated wind vector. First of all, it should be recalled that, when the vehicle is required to align to a path with a given yaw rate $r_d \neq 0$, it is not possible to steer both variables e_1 and e_2 to zero. Assuming that e_1 has a priority over the other variable, meaning that the lateral position error must vanish, the resulting steady-state value $\bar{e}_2$ is necessarily not zero. The specific value of $\bar{e}_2$ as a function of the desired yaw rate r_d can be found in [39] and is given by:

$$\bar{e}_2 = \frac{a_1}{a_1+a_2}\frac{m\,a_y}{\gamma_2} - \frac{a_2}{R} = \frac{a_1}{a_1+a_2}\left(\frac{m}{\gamma_2}u - \frac{a_2}{u}\right) r_d\,, \quad (15)$$

where the expressions for the instantaneous curvature radius, $R = u/r_d$, and lateral acceleration $a_y = u^2/R = u\,r_d$, respectively, have been used. It is worth noticing that this property arises from the nature of the physical system and is independent of the type of control used. Intuitively, the proposed backstepping approach, described below, uses the system's input $\mu = \delta$ to control the state $\xi = (\xi_1, \xi_2)^T = (\dot{e}_1, \dot{e}_2)^T$ of the velocity error subsystem, and exploits afterward such velocities to regulate the state $\eta = (\eta_1, \eta_2)^T = (e_1, e_2 - \bar{e}_2)^T$ of the position error one. This is based on the fact that the system dynamics in (1) can be written in the cascade form:

$$\begin{aligned}\dot{\eta} &= f_a(\eta) + g_a(\eta)\,\xi\,,\\ \dot{\xi} &= f_b(\eta,\xi) + g_b(\eta,\xi)\,\mu\,,\end{aligned} \quad (16)$$

where $f_a(\eta) = (0,0)^T$, $g_a(\eta) = \mathbb{I}_2$, $f_b(\eta,\xi) = (f_{b,1}, f_{b,2})^T$, with

$$f_{b,1} = \frac{\gamma_s}{m}(\eta_2 + \bar{e}_2) - \frac{\gamma_s}{mu}\xi_1 + \frac{\gamma_m}{mu}\xi_2 + r_d\left(\frac{\gamma_m}{mu} - u\right) + \frac{F_w}{m}\,,$$

$$f_{b_2} = -\frac{\gamma_m}{J}(\eta_2 + \bar{e}_2) + \frac{\gamma_m}{Ju}\xi_1 - \frac{\gamma_q}{Ju}\xi_2 - \frac{\gamma_q}{Ju} r_d + \frac{\tau_w}{J}\,,$$

and

$$g_b(\eta,\xi) = \begin{pmatrix} \frac{\gamma_1}{m} \\ \frac{\gamma_1 a_1}{J} \end{pmatrix}.$$

Following the approach developed in [40] and also described in [33], we can prove the second main result of the paper that solves Prob. 2:

Theorem 2: Given the racecar model in (1), or equivalently in (16), and given also a desired convergence speed $k > 0$ and an estimate $\hat{F} = (\hat{F}_w, \hat{\tau}_w)^T$ of the wind vector F, a backstepping-based best-effort control law for the steering angle δ, ensuring convergence of the lateral position error e_1 to zero, is given by

$$\delta = -\Gamma\left(\hat{f}_b + k\begin{pmatrix} \hat{Z}_2 + \frac{k}{4}e_1 \\ \hat{Z}_4 + \frac{k}{4}(e_2 - \bar{e}_2)\end{pmatrix}\right) \quad (17)$$

where $\bar{e}_2$ is described in (15) and where

$$\Gamma = \frac{Jm}{\gamma_1(J^2 + m^2 a_1^2)}(J, m\,a_1)\,,$$

$$\hat{f}_b = \begin{pmatrix} \frac{\gamma_s}{m}e_2 - \frac{\gamma_s}{mu}\hat{Z}_2 + \frac{\gamma_m}{mu}\hat{Z}_4 + r_d\left(\frac{\gamma_m}{mu} - u\right) + \frac{\hat{F}_w}{m} \\ -\frac{\gamma_m}{J}e_2 + \frac{\gamma_m}{Ju}\hat{Z}_2 - \frac{\gamma_q}{Ju}\hat{Z}_4 - \frac{\gamma_q}{Ju}r_d + \frac{\hat{\tau}_w}{J}\end{pmatrix}. \quad (18)$$

Proof 2: To begin with, having denoted with $\phi(\eta)$ a commanded error velocity to be designed as a feedback control law ensuring the convergence to zero of the position error vector η, and with $\delta\xi = \xi - \phi(\eta)$ the difference between the error velocity and commanded one, one can rewrite the system model in the following cascade form:

$$\begin{aligned}\dot{\eta} &= f_a(\eta) + g_a(\eta)\,(\phi(\eta) + \delta\xi)\,,\\ \delta\dot{\xi} &= f_b(\eta,\delta\xi) + g_b(\eta,\delta\xi)\,\mu - \dot{\phi}(\eta)\,.\end{aligned} \quad (19)$$

The first design step requires making the first set of variables η asymptotically stable, which is to render the first set of differential relations in (19) convergent. For this purpose, it is possible to choose the Lyapunov control function

$$V(\eta) = \frac{1}{2}\eta^T\eta = \frac{1}{2}e_1^2 + \frac{1}{2}(e_2 - \bar{e}_2)^2\,,$$

whose time-derivative is given by

$$\dot{V}(\eta) = \eta^T\left(f_a(\eta) + g_a(\eta)\,(\phi(\eta) + \delta\xi)\right).$$

Imposing for $\delta\xi = 0$ that the above expression is equal to the desired behavior, $\dot{V}(\eta) = -k\,V(\eta)$, where k is the sought convergence speed, leads to the feedback law

$$\phi(\eta) = -\frac{k}{2}\,\eta = -\frac{k}{2}\,(e_1, e_2 - \bar{e}_2)^T\,. \quad (20)$$

This ensures a convergence speed of k, which can also be seen by the fact that the first set of relations in (19) becomes $\dot{\eta} = -k\,\eta$.

Having verified that condition $\phi(0) = 0$ holds, the second design step consists in performing analogous reasoning for the stabilization variable $\delta\xi$, that is, in making the second set of relations in (19) to be convergent. To this purpose, it is worth noting that the choice of the following Lyapunov control function $V_c = V + \frac{1}{2}\delta\xi^T\delta\xi$ would be inconclusive. This occurs since the system is underactuated, i.e. it has a scalar input μ, multiplied by not right-invertible control vector $g_b(\eta,\xi)$, and a two-dimensional substate variable $\delta\xi$ to be stabilized. To overcome this problem, one can observe that g_b is left invertible for all states, which in turn implies that the matrix $\Gamma = (g_b^T g_b)^{-1} g_b^T$ always exists. Then, one can choose the Lyapunov control function

$$V_c(\eta,\delta\xi) = V + \frac{1}{2}\delta\xi^T\,\Gamma^T\,\Gamma\,\delta\xi\,,$$

which is positive semi-definite with respect to $(\eta^T, \delta\xi^T)^T$. Its time-derivative is

$$\dot{V}_c = \eta^T\left(f_a + g_a(\phi + \delta\xi)\right) + \delta\xi^T\,\Gamma^T\Gamma\left(f_b + g_b\,\mu - \dot{\phi}\right)\,,$$

where the dependency of the functions on their input arguments is avoided for brevity. Substituting in the above formula the expression of (20) yields:

$$\dot{V}_c = -\frac{k}{2}\eta^T\eta + \delta\xi^T\Gamma^T\Gamma\left(f_b + g_b\,\mu - \dot{\phi}\right)$$

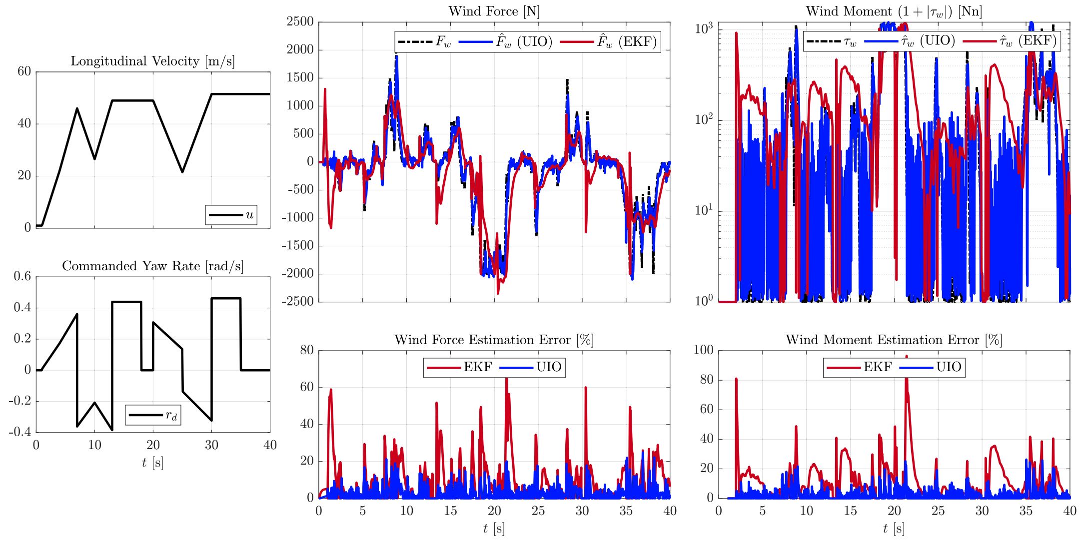

Fig. 3. Estimation Performance with Dryden wind gusts with noisy measurement: (left column) The racecar accelerates up to $\bar{u}$ = 50 m/s = 180 km/h and decelerates various times, while the road yaw rate r_d abruptly changes; (middle and right columns) wind force F_w and moment τ_w estimated by the UIO proposed in Th. 1 and an EKF. The figures show greater accuracy and faster tracking of the unknown wind signal by the UIO-based solution over the EKF.

$$= -\frac{k}{2}\eta^T\eta + \delta\xi^T\Gamma^T\Gamma\left(f_b - \dot{\phi}\right) + \delta\xi^T\,\Gamma^T\mu$$
$$= -\frac{k}{2}\eta^T\eta + \delta\xi^T\Gamma^T\left(\Gamma\left(f_b - \dot{\phi}\right) + \mu\right) ,$$

where the simplification $\Gamma\, g_b = (g_b^T g_b)^{-1} g_b^T g_b = 1$ has been used. This has first avoided the problem of non-right-invertibility of the control vector g_b multiplying input δ. By imposing now that the time-derivative $\dot{V}_c$ equals a desired behavior, namely that it satisfies the differential equation $\dot{V}_c = -k\, V_c$ finally leads to the expression

$$\mu = -\Gamma\left(f_b - \dot{\phi}\right) - \frac{k}{2}\,\Gamma\,\delta\xi = -\Gamma\left(f_b - \dot{\phi} + \frac{k}{2}\delta\xi\right) , \quad (21)$$

and also ensures a total convergence speed of k. Direct computation of the involved terms gives:

$$\Gamma = \frac{\left(\frac{\gamma_1}{m}, \frac{\gamma_1 a_1}{J}\right)}{\frac{\gamma_1^2(J^2+m^2a_1^2)}{m^2J^2}} = \frac{Jm}{\gamma_1(J^2+m^2a_1^2)}(J, m\ a_1) ,$$

and

$$-\dot{\phi} + \frac{k}{2}\delta\xi = \frac{k}{2}\begin{pmatrix}\dot{e}_1\\ \dot{e}_2\end{pmatrix} + \frac{k}{2}\begin{pmatrix}\dot{e}_1 + \frac{k}{2}e_1\\ \dot{e}_2 + \frac{k}{2}(e_2 - \bar{e}_2)\end{pmatrix}$$
$$= k\begin{pmatrix}\dot{e}_1 + \frac{k}{4}\,e_1\\ \dot{e}_2 + \frac{k}{4}\ (e_2 - \bar{e}_2)\end{pmatrix} ,$$

where Γ coincides with its expression in (18). Replacing the velocity terms and the wind vector components in (21) with the best available estimates, provided by the state-input observer described in Th. 1, i.e. $\dot{e}_1 = \hat{Z}_2$, $\dot{e}_2 = \hat{Z}_4$, $F_w = \hat{F}_w$, and $\tau_w = \hat{\tau}_w$, and then rewriting the so-obtained expression in the original state variables leads to the steering control law of (17), which concludes the proof.

Remark 1: It is worth noticing that, in general, if estimates of $\dot{e}_1$ and $\dot{e}_2$ are not available from an observer, they can still be calculated by replacing them with the corresponding equations in the dynamics. Therefore, the proposed controller uses, in any case, no information about velocities. □

V. Simulation Validation Results

This section presents a validation of the proposed estimation and control approach and compares its performance to that of existing solutions. The numerical values of the car parameters, that are typical of the cars now participating in the Roborace challenge [21], are reported in Table I. The full nonlinear car's dynamics has been implemented by using the Vehicle Dynamics Blockset of Matlab/Simulink [35].

For the purpose of showing the effectiveness of the estimator proposed in Th. 1, the following scenario has been considered. The racecar accelerates up to $\bar{u}$ = 50 m/s = 180 km/h and decelerates various times, while the road yaw rate r_d abruptly changes. A Dryden wind gust signal acts laterally to the car, starting from an initial time of t = 0.5 s. The wind speed vector is generated via Dryden's model [32], according to which the velocity of a continuous wind gust is represented as spatially-varying stochastic processes that specify their power spectral densities. Then, the corresponding wind force F_w affecting the car can be obtained via the formula $F_w = \frac{1}{2}\,\rho\, S\, c_y\, w^2$, where w is the crosswind speed, $\rho = 1.225\frac{Kg}{m^3}$ is the density of air at sea level, S is the reference area and c_y is the lateral force coefficient. The wind moment τ_w is computed as the net moment applied over the entire lateral car's surface. The lever arm $l \in [-a_2, a_1]$ of the wind force F_w is also randomly generated so as to obtain the instantaneous wind moment $\tau_w = l\, F_w$. Noise is added to the lateral and orientation error positions as white signals with zero mean value and standard deviations of 0.01 m and 0.017 rad, respectively, to simulate measurements. (cf. e.g. [41]). Fig 3 illustrates how the proposed UIO can promptly and accurately reconstruct the wind's force and moment. It also shows how it outperforms an EKF [31], which, analogously to the proposed UIO, includes a system model inversion scheme to retrieve the unknown wind signals. This choice correctly ensures that the derivations of both the UIO and the EKF are independent of the mathematical wind model. It is noticeable that the UIO remains accurate even in the presence of measurement noise.

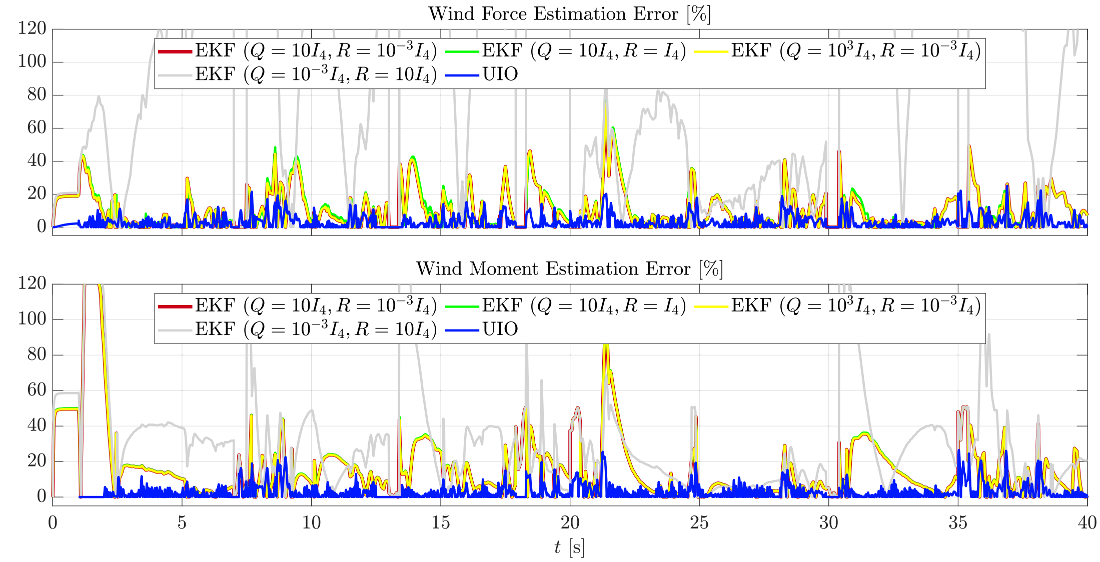

Fig. 4. Performance comparison in estimating Dryden wind gusts by the proposed UIO (Th. 1) and the EKF for various process and measurement noise. The percentage of the wind force F_w and moment τ_w estimation errors are reported in the top and bottom rows, respectively, for the UIO (blue) and the EKF with $Q = 10I_4$ and $R = 10^{-3}I_4$ (red), with $Q = 10I_4$ and $R = I_4$ (green), with $Q = 10^3I_4$ and $R = 10^{-3}I_4$ (yellow), and with $Q = 10^{-3}I_4$ and $R = 10^3I_4$ (gray). Greater accuracy and faster tracking of the unknown wind signal by the UIO over all EKF are shown.

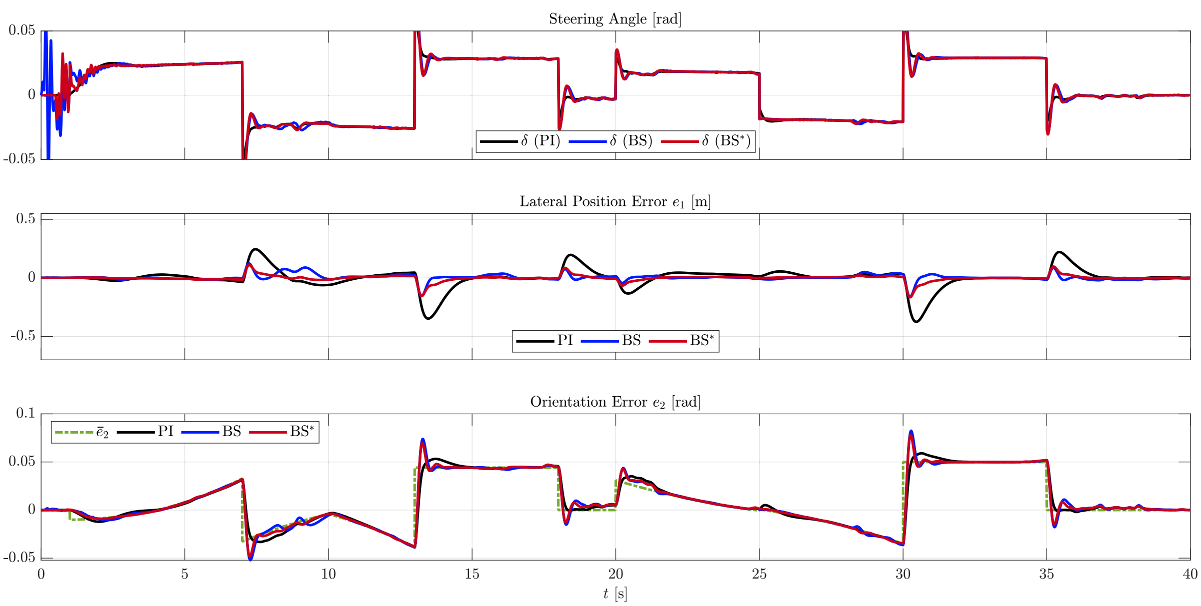

Fig. 5. Controller's Performance with UIO-based Closed-loop Estimation: The racecar is performing the same maneuver as in Fig. 3, while the estimates of the unknown wind signal $\hat{F} = (\hat{F}_w, \hat{\tau}_w)^T$ and state variables, obtained via the proposed UIO, are used to determine the steering signal δ according to Th. 2 (first row); the second and third rows show how the commanded orientation error $e_{2,c}$ is accurately tracked by e_2 and the lateral error e_1 is kept close to zero. It is worth noticing that the proposed backstepping controller (BS*) has a faster rise time and smaller overshoot than the other two controllers (cf. the detail in the first-row plot), thereby achieving faster and more accurate tracking (second and third plots).

Furthermore, it is worth comparing the performance of the proposed UIO (Th. 1) and an EKF-based approach. Referring to Fig. 4, it can be seen that the UIO achieves higher accuracy and faster tracking in the estimation of unknown Dryden wind gusts compared to EKFs that are tuned with various combinations of process and measurement noise. The superior performance of the UIO is supported by at least the following: firstly, it does not rely on assumptions about the dynamic nature of the disturbances affecting the system, whereas the EKF is designed on the assumption that these disturbances (process and measurement noise) are zero-mean, white and stationary; in addition, the EKF does not guarantee zero convergence for state estimation errors, whereas the convergence of the UIO, even in a closed loop, is ensured by the input decoupling property obtained by design; finally, the EKF approach is case-dependent and requires parameter tuning based on the specific system under consideration, whereas the UIO design is generally applicable *as is* for any system satisfying the existence conditions.

Moreover, to prove the effectiveness of the backstepping controller proposed in Th. 2, and in fact of the entire solution of this paper, the racecar system is closed in the loop with

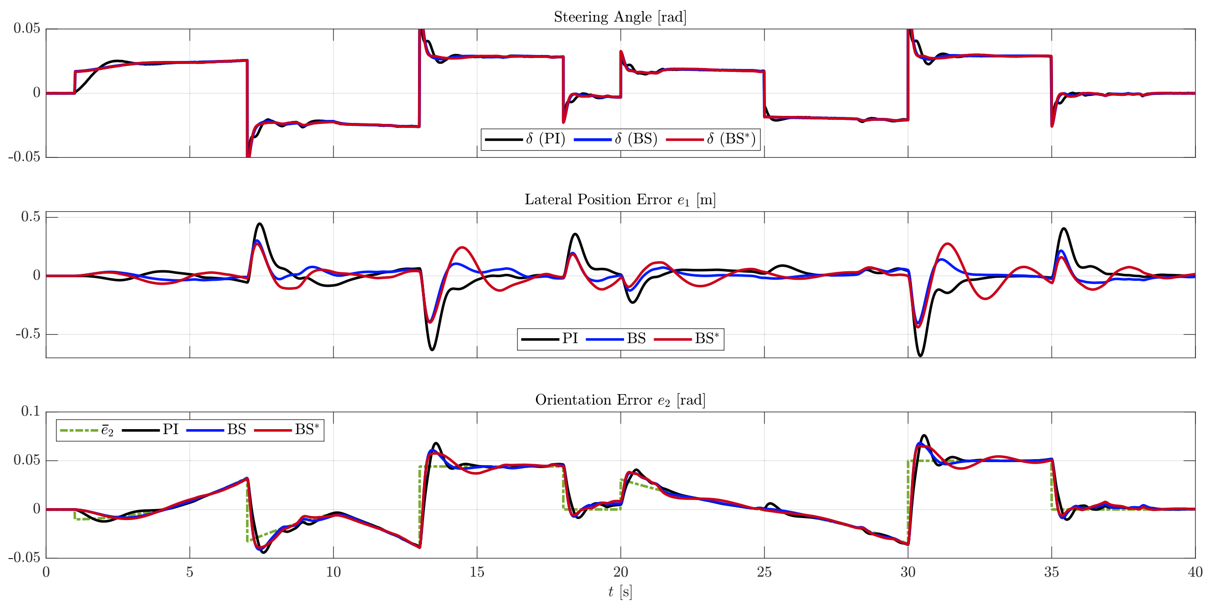

Fig. 6. Controller's Performance with EKF-based Closed-loop Estimation: The racecar is performing the same maneuver as in Fig. 3, while the estimates of the unknown wind signal $\hat{F} = (\hat{F}_w, \hat{\tau}_w)^T$ and state variables are obtained via the EKF. It can observed that EKF-based controllers work worse than UIO ones; moreover, the proposed backstepping controller (BS*) has better performance than the other two.

such controller and the input-state estimator of Th. 1. The performance of the present controller is compared to those of a traditional PI controller [33] and the backstepping controller proposed in [34] (later referred to as BS). Compared to the former, the current backstepping approach symmetrically regulates both linear and angular position errors, during the first step of design (cf. the theorem's proof), instead of only the linear one. Fig. 5 illustrates the obtained results and shows how our controller, referred to in the figure as BS*, successfully allows tracking the desired path, irrespective of the wind presence and the road curvature. As expected from [39], the steady-state orientation error is given by (15). It can finally be noticed that our backstepping controller has a faster rise time and smaller overshoot than the other two controllers (cf. the first-row plot), thereby achieving faster and more accurate tracking (the second and third plots). Finally, Fig. 6 reports the results obtained with the three considered controllers, using the EKF estimates. It can be observed that EKF-based controllers work worse than UIO ones; moreover, the proposed backstepping controller (BS*) has better performance than the other two.

VI. Conclusion

This work addressed the problem of estimating and compensating wind gusts for a racing car. It proposed an innovative solution based on UIO theory and backstepping control. Despite the simplicity of the described linear state-input estimator, the proposed approach proved to be able to quickly reconstruct even wind vector signals rich in frequency components, such as those generated by a Dryden gust model. In addition, the backstepping-based controller is able to compensate for the effect of the wind and guarantee any desired convergence speed for the lateral positional error. The solution was validated through simulations with characteristics similar to those of the vehicles competing in the Roborace challenge. The results show that the proposed estimator outperforms an EKF, and the proposed backstepping controller better compensates for the effect of wind. While the current work focused on side wind gusts, future work will consider the entire system dynamics with winds coming from any direction.

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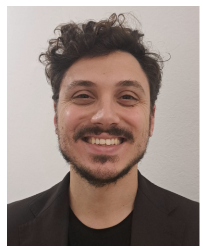

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